

Glacial Lake Observatory (GLO): Annual dataset of glacial lakes in Nepal and transboundary catchments (2017–2024)

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Response to Reviewer 1

This study presents an annual glacial lake dataset spanning 2017 to 2024, mapping lake extent and quantifying lake area change across an 8-year study period using imagery from both Sentinel-1 and Sentinel-2. Image processing was conducted in Google Earth Engine, with Sentinel-1 annual median mosaics derived from July and August acquisitions and Sentinel-2 composites covering May to November with a cloud cover threshold of 60% at 10 m resolution. Model training employed the DeepLabV3 architecture within ArcGIS, with a training dataset constructed from manual digitizations for the year 2020 from previously published datasets. Post-processing is applied to remove unnatural water bodies based on a digital elevation model. Validation was performed against both manually digitized lakes and published datasets. Sentinel-2 derived results showed higher lake counts compared to Sentinel-1 derived lakes. Hence, the lake area detected based on optical imagery was higher than from SAR imagery. Both sensors performed better for larger lake sizes with smaller errors. The authors' planned glacial lake observatory, which aims to monitor lakes on an annual basis, is a commendable and timely initiative that has the potential to make a valuable long-term contribution to the glaciological community.

The manuscript is well written, clear, and methodologically detailed, and provides useful analyses of lake number, lake area time series, and elevation distribution. Nonetheless, several aspects of the manuscript would benefit from further clarification and discussion, particularly a more thorough examination of dataset limitations and the underlying reasons for the observed differences between lakes mapped from optical and SAR data.

We thank the reviewer for their overall positive comments to the manuscript and glacial lake dataset.

We appreciate that there is room for further clarification and discussion, in particular regarding dataset limitations and observed differences between optical- and SAR-extracted glacial lakes. We have now expanded on this with the addition of **Sect. 5.3.2. Recommended use and detection limits** (see page 8 of this reviewer document).

Specific comments:

Figure 1: Consider putting the coordinate system only around the map and the plots outside the map frame.

Thank you. We have now amended Figure 1, so the coordinate system is only around the map (and plots on the outside).

Table 1: Consider to add your own dataset into this table and highlight what makes your dataset novel/different from existing ones.

Thank you for this suggestion. We have now added our dataset into this Table (1).

L126: Outline more clearly (or create a map) how the training, evaluation and manually digitized lake data is spatially distributed. Not being familiar with the GTN-G regions it is hard to understand where the data is located and if the training and evaluation data is spatially overlapping in any kind.

We have moved Line 85 which first mentions GTN-G regions to Section 3.1 to provide some more detail as to what the GTN-G regions are (with reference to this framework) and clearly stated which ones were used and why. The subsequent text has been added.

'To align with the standardised Global Terrestrial Network for Glaciers (GTN-G) framework for internationally coordinated glacier monitoring (GTN-G, 2023), fifteen GTN-G second order (O2) regions spanning High-Mountain Asia (regions 13-01 to 13-09, 14-01 to 14-03, and 15-01 to 15-03) were selected for image acquisition and model development and are shown in Figure S1. This full, regional coverage ensured that model training captured the broad climatic, glaciological and spectral variability characteristic of the region to enhance model

robustness. Subsequent model refinement and validation were then focussed on the Nepal-transboundary study region (GTN-G regions 15-01 and 15-02; with a 200 m overlap into region 13-08) to best test and compare the model with pre-existing lake inventories and manually digitised validation data available for this region.'

We have also added an additional panel into Figure S1 in the supplementary information showing the spatial distribution of the manually digitised dataset for validation (Fig. S1b), alongside the GTN-G 02 regions (Fig. S1a).

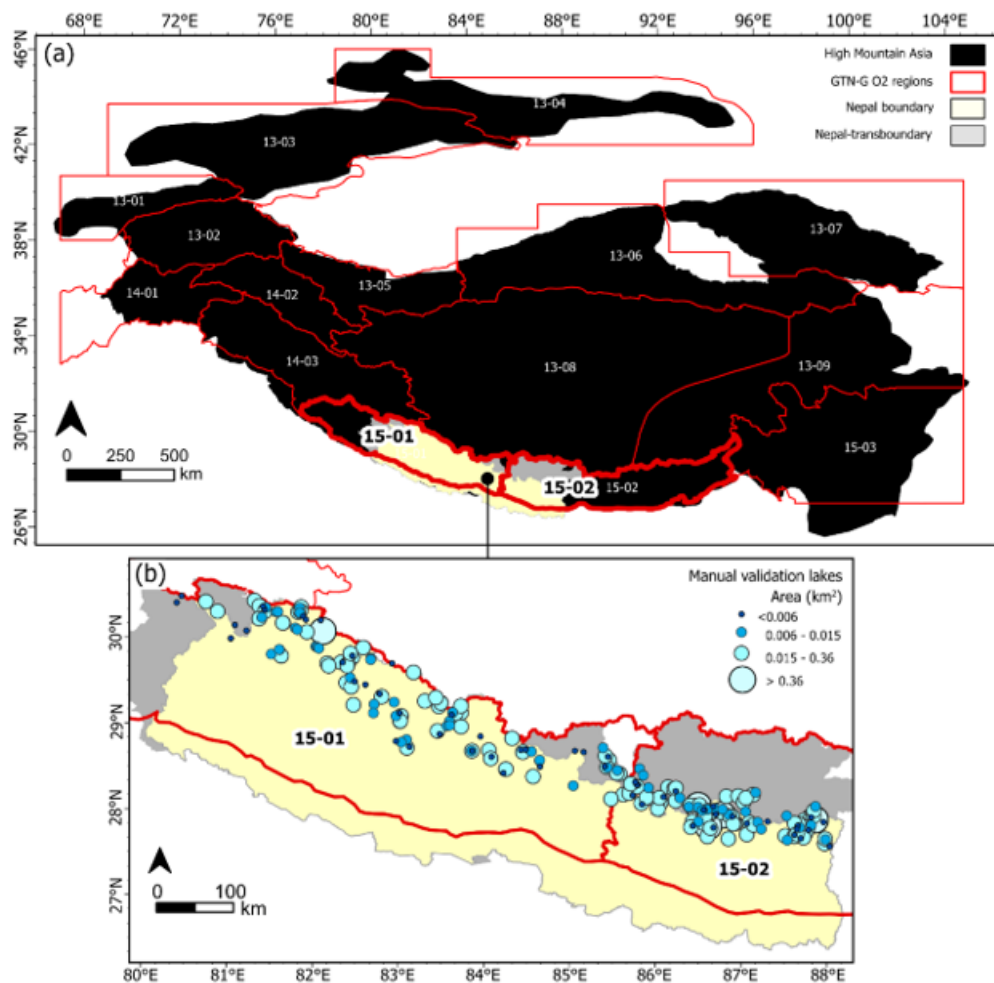


Figure S1: (a) The Global Terrestrial Network for Glaciers (GTN-G) O2-regions for High Mountain Asia (HMA; GTN-G, 2023). The Nepal-transboundary glacial lake dataset spans the O2-regions of 15-01 and 15-02 (Central Himalayas) with a 200 m overlap into 13-08. HMA outline from Bolch et al. (2019); (b) The coverage of the manual digitised dataset used for deep learning validation, showing a spatially variable and representative sample of lake sizes across the Nepal-transboundary region.

L133 & L140: Annual mosaics for Sentinel-1 (Jul-Aug) and Sentinel-2 (May-Nov) are created over different time periods. Are there any intra-annual/seasonal variations in the lake area that could be mapped differently due to this difference in time period? Maybe something difficult to quantify but worth discussing in a limitations section.

Thank you for this comment. We acknowledge that the annual mosaics for Sentinel-1 and -2 were generated for different time windows and therefore some lake extent variability may occur. For example, supraglacial lakes reaching their maximum extent in the pre-monsoon (Zeller et al., 2024). These differing time periods were selected for the following reasons:

- (1) Sentinel-1 mosaics had a more restricted time window (July-August) to prioritise acquisitions when glacial lakes are most likely to be ice-free. A broader time window was not required for Sentinel-1 since all images were expected to capture the lake surface irrespective of cloud cover. Additionally, Sentinel-1 data were used to complement optical observations under conditions where optical

observations may be limited and the potential for some smaller, higher altitude lakes to still be frozen and go unmapped.

- (2) Sentinel-2 mosaics were generated over a broader time window (May-November) to maximise the availability of cloud-free observations within this cloud affected, monsoon region. Extending this composited time period therefore improved optical data availability and reduced data gaps, particularly during the monsoon season.

We have now added in some additional justifications to the following:

Sect. 3.1.1:

‘A smaller date range was used compared to Sentinel-2 processing (Sect. 3.1.2), as the Sentinel-1 backscatter is not affected by cloud cover, allowing for more images to be available for compositing during the post-Monsoon period when lakes are typically ice-free and near their seasonal maximum extent. Whilst some lake extent variability may occur due to these time window differences per sensor, Sentinel-1 data is intended to be complimentary by contributing temporally when optical observations are limited.’

And Sect. 3.1.2:

‘All available Sentinel-2 images (L1C) were used within the date range of May to November for years 2017 to 2024. This broader date range was used to coincide with the Monsoon season and late-ablation period, when the surface of glacial lakes is typically unfrozen, while also maximising the availability of cloud-free observations and reducing spatial data gaps in this persistently cloudy region.’

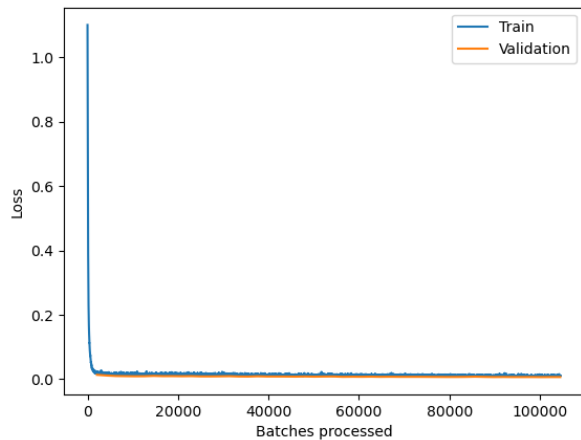
L153ff: Justify in more depth why you chose DeepLabV3 as deep learning model. E.g. did other studies come to the conclusion that this model works best? Maybe give the reader a bit more in-depth information about DL methods that have been used for lake mapping and how well they performed (e.g. by extending from line 57 onwards on the DL methods).

Thank you for this comment. We have now expanded the manuscript to provide a clearer rationale for the selection of the DeepLabV3 model (ResNet50 backbone), including information about other models that were tested – see additional text below. Reference to applicable literature is additionally given.

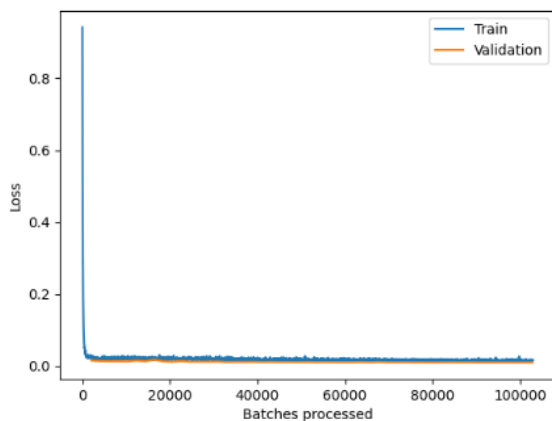
‘Deep learning models such as U-Net, originally designed for biomedical image segmentation (Ronneberger et al., 2015), or DeepLabV3 for semantic segmentation (Chen et al., 2017), are increasingly used for a broad range of geoscience classification tasks. For glacial lake mapping, DeepLabV3 is already a well-supported model choice, with previous studies demonstrating its performance for lake detection across heterogeneous mountain environments (Siddique et al., 2023; Tang et al., 2024; Xu et al., 2024). U-Net has also shown promise for glacial lake detection, particularly in localised remote environments (Ali et al., 2025; Sharma et al., 2024), however some challenges with frozen surfaces, small lake separation and boundary accuracy in diverse mountain terrain have been noted (Cao et al., 2025; He et al., 2021; Tang et al., 2024). In preliminary testing for this study, both U-Net and DeepLabV3 models were evaluated using the same training data, a variety of spectral bands (and indices) and comparable backbone configurations, with both models achieving the same F1 scores (0.85), although U-Net required approximately twice the inference runtime of DeepLabV3. SAMLoRA (ViT-H backbone) was also evaluated with the same input data and spectral bands, and again produced a comparable F1 score (0.80) but required more than four times the inference runtime than DeepLabV3. As a result, DeepLabV3 was selected, as this model provided a favourable balance between segmentation accuracy and computational efficiency, ideal for scaling up to larger geographical areas. Additionally, its combined architecture of atrous (dilated) convolution and atrous spatial pyramid pooling (ASPP) makes it capable of classifying features across a range of scales and with complex backgrounds (Chen et al., 2017).’

L165: How did you decide on training for 50 epochs? Did you use the model weights after 50 epochs or after early stopping based on validation loss? It would be very helpful to have accuracy and loss curves of the training in the appendix to see how the model converged and whether it over/underfitted. Usually, it is recommended to use the model with the lowest validation loss instead of a model trained after a fixed number of epochs.

We selected 50 epochs based on observations from early pilot runs, where improvements became marginal for later epochs. To maximise the dice score, while still avoiding excessive training, we chose 50 epochs as a reasonable upper bound. The Sentinel-2 model used was epoch 47, which corresponded to a 42.9% increase in the dice score over training period.



The Sentinel-1 model was used from epoch 49, which corresponded to a 24.8% increase in dice score over the training period.



L170: At this point it is difficult for the reader to understand how the power-law model was derived without having seen the numbers of the manual validation dataset in the later section. Consider re-structuring sections or give a bit more in-depth information already from L170 onwards to clarify.

We have added the following text in this section to provide additional detail before the manually digitised datasets are introduced in Sect. 3.4.2.

‘For each lake, false positive and false negative areas were calculated by intersecting the model output with the manually digitised lake outlines (Sect. 3.4.2). The total area error was defined as the sum of these false positive and false negative areas and expressed as a percentage of the manually digitised lake area. The relationship between area uncertainty and lake size was used to fit a power-law model, which was then applied to the model outputs to estimate uncertainty in lake delineation (Eq. 1).’

L185: What is the acquisition date of the DEM you used? Is it possible that anomalously elevation deviations you are masking out could have occurred due to glacier retreat that occurred after the DEM was acquired? Maybe also something for a discussion in the limitations section.

The ALOS Global Digital Surface Model V4.1 used in this study is derived from stereo imagery acquired from 2006 to 2011. Version 4.1 incorporates void filling and anomaly correction using Copernicus DEM GLO-30 and ArcticDEM v4 (JAXA, 2024)

We acknowledge that glacier retreat and surface lowering will have occurred across Nepal (and High Mountain Asia as a whole) since 2011 and so this could introduce some elevation discrepancies between the DEM and imagery used here. For post-processing, the DEM was used to extract elevation statistics (minimum, median, mean and standard deviation) for each mapped glacial lake polygon as a topographic consistency check, with a -10 m buffer applied to each lake polygon to reduce the potential of mixed pixel edge effects – this has been further clarified in Sect. 3.3 and can be seen below.

Standard deviation was primarily used for this purpose as lake surfaces are expected to be approximately planar, therefore there should be low elevation variability. Lakes that display a high elevation standard deviation is indicative of the incorporation of steep valley slopes or other non-water terrain, representing a misclassification. A conservative threshold of std >50 m was applied to assist in removing these inconsistent outlines; this threshold was intentionally not restrictive in order to avoid excluding true lake polygon delineations. Although glacier thinning and retreat since 2011 may result in some elevation change, such changes are unlikely to produce large elevation variability within a lake basin (and a correctly mapped polygon).

‘Additional attributes were added to the lake database (Table 2) including area and perimeters derived in an ESRI:102025 - WGS 1984 Albers for Northern Asia projection, corresponding river basin locations (Koshi, Gandaki, and Karnali) using basin outlines from ICIMOD (ICIMOD, 2021) and elevation statistics (minimum, mean, median and standard deviation) derived from the AW3D30 DSM V4.1 (Tadono et al., 2014) using buffered (-10 m) lake polygons to assist with the reduction of mixed pixel edge effects on such statistics. No manual editing of the lake outlines was undertaken; however, we removed (i) erroneous classifications at the overlapping edges of composite imagery; (ii) the Shey Phoksundo landslide dammed lake (82°56'58"E, 29°11'33"N) and; (iii) lakes with anomalously high elevation standard deviations (e.g., > 50 m) indicative of false positives (e.g., increased error on steep slopes, obscurement by shadows) or DSM artefacts: *a conservative threshold that was less restrictive in order to avoid excluding true lake polygon delineations*. A total of 856 lake polygons, or 4% of the dataset, were removed from the final dataset across the eight-year study period.’

L182: You use the RGI (which version?) dataset to distinguish between glacier fed and non-glacier fed lakes. The RGI provides glacier outlines for the year 2000. Discuss how this influences your categorization and which uncertainties arise from this.

It is stated in Sect. 2 that RGI v7.0 South Asia East glaciers (RGI Consortium, 2023) within the boundary of Nepal and transboundary catchments was used for deriving glacier-fed and non-glacier-fed lake characteristics. This is the most up-to-date RGI dataset at this time and is a spatially consistent glacier inventory that is currently available and used for High Mountain Asia. Although there are temporal limitations to using RGI outlines (i.e., glacier retreat since 2000), classification in this study is based on upstream glaciers and flow accumulation/routing, rather than direct glacier terminus contact. This is therefore unlikely to alter lake categorisation unless a glacier has disappeared.

L187: It would be helpful to either provide a visual example about the errors in overlapping regions or describe in more detail what kind of errors there are and how you remove them.

Thank you for this suggestion.

A visual example is now provided in the supplementary information – Figure S2 (see below), to further show overlapping regions and why certain erroneous polygons were removed.

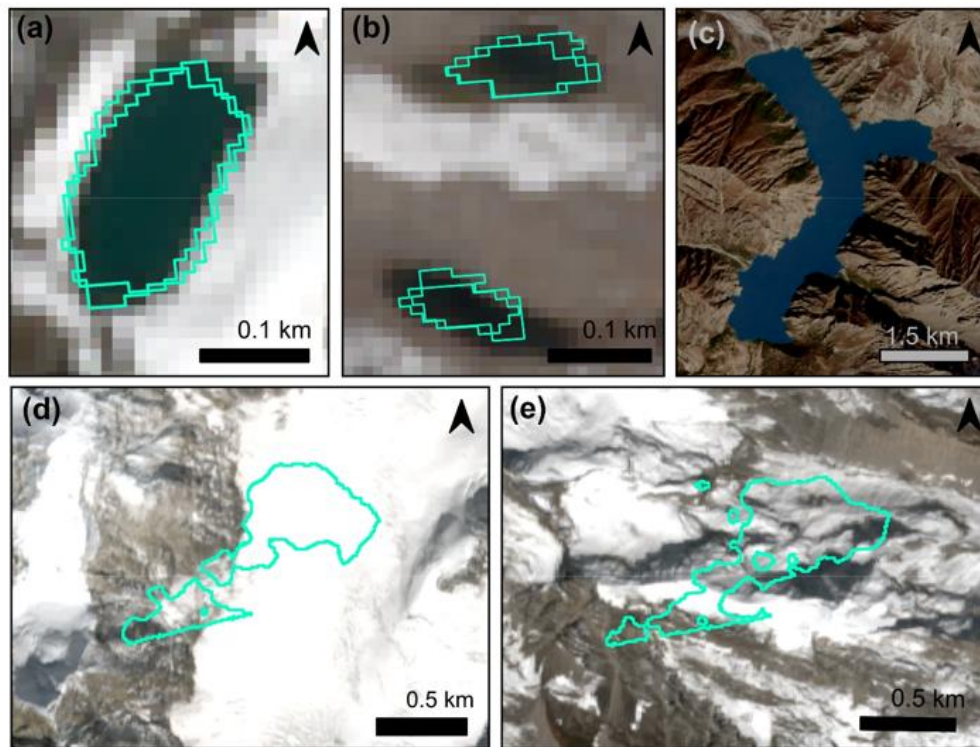


Figure S2: Examples of lake detections removed from the glacial lake dataset. Both (a) and (b) show glacial lakes which detected twice due to slight spatial offsets between adjacent image tiles. These were identified and removed via repeat GLO_IDs. (c) The Shey Phoksundo landslide lake which was removed from the dataset; (d) and (e) erroneous polygons captured on mountain terrain, removed using high elevation std values.

In essence, lakes located along image tile boundaries were detected twice due to overlap between adjacent image tiles. These duplicates or partially overlapping regions were easily identified through repeat GLO_IDs and were removed. Other erroneous polygons included the presence of overly large and irregular shaped polygons positioned over mountainous terrain that were clearly not lakes. Again, these were identifiable through high std elevation values and removed. The Shey Phoksundo lake (82°56'58"E, 29°11'33"N) was removed as this a large landslide-dammed lake rather than a glacial lake formed as a result of glacier thinning or retreat.

L215: Intersection over Union (IoU) could be an interesting additional evaluation metric to see how well the different lake datasets geometrically overlap.

Whilst IoU values are provided in Table S2 and Table S3 in the Supplementary Information, we agree that its inclusion in the main body of text is a valuable addition. These values have now been added into Sect. 4.1.1 and Sect. 4.1.2 for both Sentinel-1 and -2. See added text below.

Sect. 4.1.1

‘First, comparisons with Zhang et al. (2024a) found good agreement in detections between the datasets, resulting in F1 scores of 0.82 for Sentinel-1 and 0.87 for Sentinel-2 (Table S2), with corresponding IoU values of 0.70 and 0.78, respectively.’

Sect. 4.1.2

‘When compared against the combined Zhang et al. (2024a) and Kumar et al. (2025) inventories the F1 scores were slightly lower, with 0.79 and 0.85 for Sentinel-1 and -2 respectively, with corresponding IoU values of 0.66 and 0.74. Again, these results demonstrate good spatial agreement across datasets of differing sensors.’

L237ff; L339ff & L499ff: Discuss in more detail why lakes have been mapped differently by Sentinel-1 and Sentinel-2. Why are accuracies lower for Sentinel-1? Why remained lake numbers more stable based on Sentinel-1 compared to Sentinel-2? A discussion including sensor specifics would probably be very helpful so

the user of the dataset knows better what kind of lakes are mapped best by which sensor. E.g. do you have visual examples of lakes that were mapped in Sentinel-2 imagery but not Sentinel-1 imagery? How do these lakes look like in both images and why wasn't it possible to map them from Sentinel-1 imagery? What is the recommendation for the user regarding the S1/S2 datasets? Use both in combination or prefer one over the other in specific cases?

Please see previous comments above (page 3) for our reasoning of mapping lakes for differing time periods for Sentinel-1 and -2. This has now been discussed further in the new **Sect. 5.3.2** (see page 7 of this document) to more explicitly describe why lake delineations differ between the two sensors, why Sentinel-1 accuracies are lower and lake counts different.

In summary, (i) lakes in Sentinel-1 likely remained more stable through time due to a combination of factors. (i) A smaller compositing date range for Sentinel-1 was used, meaning lakes were more likely to be captured at a similar time each year; (ii) Sentinel-1 had greater omission for smaller lakes and required a larger lake size threshold to achieve robust performance than Sentinel-2 (0.084 km² versus 0.028 km²). This interpretation is also consistent with the lower agreement of Sentinel-1 with external inventories ($F1 = 0.79\text{--}0.82$) relative to Sentinel-2 ($F1 = 0.85\text{--}0.87$). As a result, there would be less fluctuation due to the seasonal changes in these smaller lakes that are intermittently captured in Sentinel-2 but not Sentinel-1; (iii) median composites of Sentinel-1 are more likely to exclude smaller lakes that are changing in shape, position (e.g. Kumar and Vijay, 2026), or with variable backscatter due to the presence of ice or waves. However, there is a lack of published datasets, for example providing coincident Sentinel-1 and higher resolution observations (e.g. PlanetScope) to fully quantify sensor performance.

In terms of visual examples of sensor-specific delineations, Figure S4 in supplementary information provides examples of Sentinel-1 vs -2 lakes, in particular highlighting areas where Sentinel-1 captured snow-buried lakes (and where Sentinel-2 of course omits them as they were not optically-present) and Fig.3 showing an example in time-series outlier where a large lake delineation was affected by surface ice/icebergs in Sentinel-2, but was completely captured in Sentinel-1.

To additionally show where Sentinel-2 captured lakes that Sentinel-1 did not (and the opposite), we have now added an additional figure into supplementary information (Fig. S5). For user recommendation, we would suggest considering both inventories but consider Sentinel-2 as the primary dataset due to the higher overall accuracy. Where outliers are apparent in one dataset, a user could cross-reference with the other.

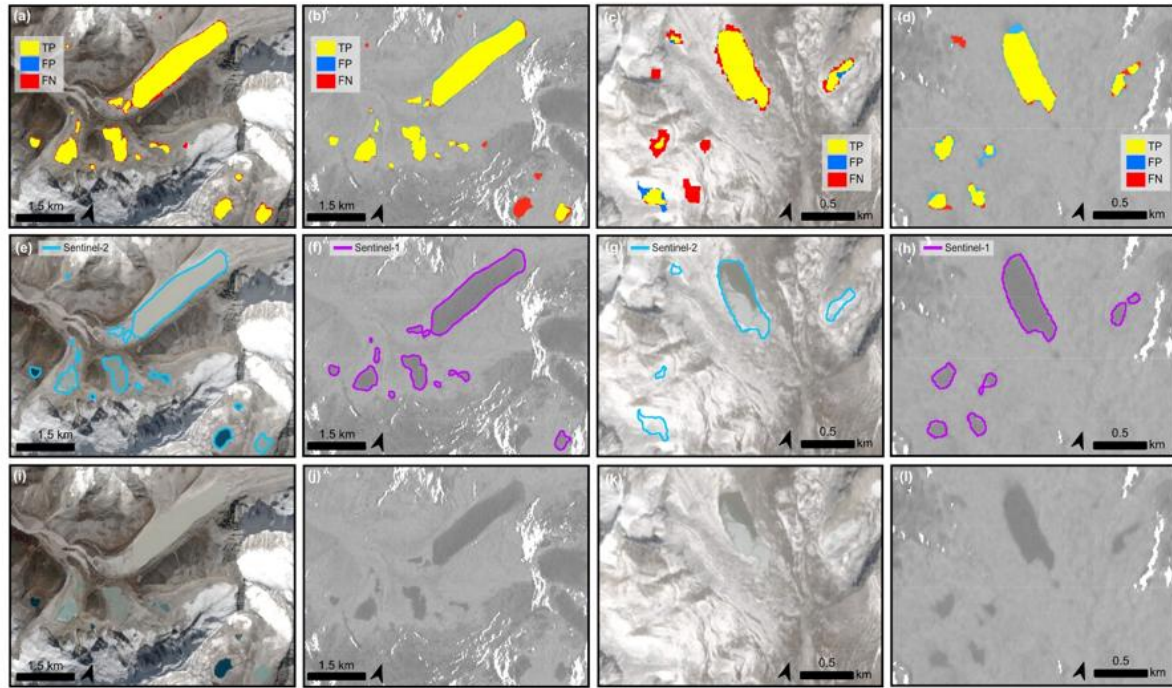


Figure S5: Examples of deep learning classification performance relative to reference inventories for Sentinel-2 and Sentinel-1 (2020) and subsequent lake delineations overlain on Sentinel-2 RGB and Sentinel-1 SAR training imagery. (a-d) True positives (TP), false positives (FP), and false negatives (FN), with left-hand pair (a,b) showing better performance in Sentinel-2, whereas right-hand pair (c,d) showing better performance in Sentinel-1 where snow and ice are more prevalent; (e-h) Corresponding model lake outlines overlain on 2020 training imagery; (i-l) corresponding imagery only.

L440: A limitations section in the discussion would be very helpful so the user knows what the dataset can/cannot provide.

Whilst we do acknowledge some limitations in Sect. 5.1, we have now expanded this into a new section **Sect.**

5.3.2. Recommended use and detection limits. See full text below:

5.3.2 Recommended use and detection limits

The dataset produced here provides a consistent and reproducible inventory of glacial lakes across the Nepal-transboundary region across the eight-year study period, making it well suited to regional-scale assessments of lake distribution, presence/absence, and broader interannual change. As with any regional-scale inventory, data confidence varies according to lake size and sensor type. Although a minimum mapping threshold of 0.001 km² was applied in this study, classification performance remains largely size dependent. For Sentinel-2, robust performance ($F1 \geq 0.85$) was generally achieved for lakes of above 0.028 km², whilst for complimentary data provided by Sentinel-1, a larger size threshold of 0.084 km² was required to reach the same classification performance ($F1 \geq 0.85$). A multiple linear regression model further showed that lake area was a dominant control on F1 score for both sensors, whilst elevation exerted a very small secondary influence. For Sentinel-2, the effect was weakly negative and statistically significant ($p = 0.02$), but of negligible magnitude, whereas for Sentinel-1 this was not significant. Together, these results indicate that reduced performance in small, often high-elevation lakes is driven primarily by lake size and the difficulty of complete delineation, rather than elevation itself acting as a strong independent control.

That said, small, irregular and high-elevation lakes do remain particularly challenging due to increased mixed pixel boundaries of water, snow and ice, combined with steep terrain and seasonal partial freezing (Kumar and Vijay, 2026; Qayyum et al., 2020; Watson et al., 2018). This likely explains the slightly lower agreement observed when lake comparisons included the Kumar et al. (2025) inventory, which contained a greater proportion of smaller lakes near the minimum mapping threshold (0.001 km²). Additionally, some smaller lakes are highly ephemeral (e.g., supraglacial lakes) and may partially drain or disappear during the compositing period. In this case, while it would appear as a false negative when compared to Kumar's dataset, it is in fact a true negative, as

the lakes were absent at the time of observation. In this context, higher-resolution imagery such as PlanetScope may support improved delineation for small or irregular lakes by resolving these mixed-pixel edge effects (Xu et al., 2024). However, this capability relies on quota-limited free research-programme data access, or paid access to the commercial dataset (<https://www.planet.com/industries/education-and-research/>) and may be most effectively applied to targeted training data or validation.

In terms of sensor specifics, the two sensors provide strengths for glacial lake monitoring. Sentinel-2 is shown to be better suited to the accurate delineation of individual lake boundaries, including smaller lakes, and should therefore be considered the primary dataset for more detailed and complete lake mapping. Sentinel-1 provides a valuable complimentary perspective by offering more consistent, all-weather observations, assisting with supplementing optical data gaps (i.e., the capture of lakes during monsoon or cloudy periods) and improve visibility of snow-or-ice covered lakes (Fig. S4; Fig. S5). It is noted, however, that these Sentinel-1 delineations are more prone to fragmented or irregular lake outlines, particularly for smaller lakes, likely reflecting known SAR challenges including speckle noise, look direction, incidence angle and backscatter variability over water and rugged terrain (Khan et al., 2025; Miles et al., 2017). At the same time, the Sentinel-1 dataset provided more temporally consistent lake counts, which is a likely reflection of a combination of factors: (i) the narrower acquisition compositing window meaning lakes were more likely to be captured at a similar time each year; (ii) a greater omission of smaller lakes, reducing year-to-year variability in the seasonal changes of smaller lakes, that are then intermittently captured by Sentinel-2; (iii) the use of median SAR composites which are more likely to exclude small, highly dynamic lakes (Kumar and Vijay, 2026). As such, Sentinel-1 should be interpreted as reflecting a more conservative subset of lake detections, rather than completeness. Finally, the annual Sentinel-1 and Sentinel-2 mosaics were generated from different acquisition windows to balance the observational capabilities and data availability of each sensor, so some minor differences between the two datasets may reflect differences in temporal sampling. Additionally, the Sentinel-1 model was trained using lake outlines derived from optical imagery (Kumar et al., 2025; Zhang et al., 2024) which may introduce some minor boundary mismatch between training labels and the SAR signal. Given the current lack of SAR-based training data, this approach is a reasonable compromise for Sentinel-1 model development and highlights an important avenue for future model refinement using SAR-based training labels. Beyond the overall strong performance shown of both sensors in this study, and the known limitations, ongoing work will set to further refine the classification models, with additional training and inference planned for the wider Himalayan region.

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Response to Reviewer 2

This study presents a new annual glacial lake dataset for Nepal and adjacent transboundary catchments covering the period 2017–2024. The authors use multi-sensor satellite imagery from Sentinel-1 and Sentinel-2 to map lake extent and quantify changes in lake area over time. Image processing was conducted in Google Earth Engine, and lake detection was performed using a DeepLabV3 deep learning model trained on previously published manual inventories. The dataset is validated against manually digitized lakes and existing inventories, showing generally strong performance, particularly for larger lakes.

I really enjoyed reading this paper. I think it is a strong contribution and will be very useful for the community. The manuscript is well written, clearly structured, and the methods are explained clearly.

That said, I believe there are a few aspects that should be clarified so that users of the dataset can better understand the methodological limits and avoid potential misinterpretations.

We thank the reviewer for their overall positive comments and that they enjoyed reading paper.

We appreciate there are some aspects to be clarified, including methodological and dataset limitations, which align with reviewer 1, and we have now included a new limitations section (**Sect. 5.3.2 Recommended use and detection limits**), which is provided on page 2.

We have further expanded on specific points below.

Specific comments:

1 – it would be helpful to be more explicit about detection limits and methodological biases. While the nominal threshold is 0.001 km², the validation shows that small lakes have much higher relative uncertainty. It would strengthen the paper to **clearly state what lake sizes can be reliably monitored for change analysis**, and where **uncertainty becomes too large for robust interpretation**. Similarly, lake surface ice and partial freezing are mentioned as sources of error, but it would help to specify when and where this is most problematic (e.g., elevation bands, specific basins, certain months). Without this, users might overinterpret trends in small or high-elevation lakes. A short paragraph summarizing recommended use and limitations would be very useful.

Thank you for your comment. We agree that uncertainty does increase for lakes approaching this threshold of 0.001 km². To further expand on this uncertainty and reliability of lake sizes for change analysis (including for both Sentinel-1 and -2), we have added some further robustness analysis (lake area and elevation) and included associated methods in Sect. 3.4.2, its results in Sect.4.1.2 and further discussion in Sect. 5.3.2 (see added text below). This is an expansion of some limitations that were originally mentioned in Sect. 5.1, which have now been collated into this new section.

In short, the results of this robustness analysis show a size dependence of 0.028 km² and 0.084 km² for Sentinel-2 and Sentinel-1 respectively is required to achieve robust classification performance ($F1 \geq 0.85$). Low F1 scoring lakes were associated with smaller lakes at slightly higher elevations, as one would expect. In terms of controls on F1 score, size was shown to have a strong positive and significant relationship, whilst elevation had a weak non-significant negative effect.

Whilst we do acknowledge some limitations in Sect. 5.1, we have now expanded this into a new section **Sect. 5.3.2. Recommended use and detection limits**. See full text below.

In terms of whether specific basins posed problems for lake delineation, no significant effect of basin on F1 score was detected, and the sensor-specific difference in F1 did not vary significantly among basins, so this was not explored further.

Sect 3.4.2:

‘Further validation analysis was also undertaken to assess classification robustness as a function of lake size and elevation for both Sentinel-1 and Sentinel-2 data. For size-dependent performance, F1 scores were examined across lake area and used to identify the approximate minimum lake size at which robust classification ($F1 \geq 0.85$) was achieved. For the influence of elevation on classification performance, median elevation was extracted for each lake polygon (-10 m buffer) using the AW3D30 DSM (Tadono et al., 2014) and a multiple linear regression performed to assess the effects of lake area and median elevation on F1 score for the sensor-comparable years of 2020.’

Sect 4.1.2:

‘This size dependence of lakes is also used to approximate the threshold at which robust classification performance of the model is reached. For Sentinel-2, a robust performance score ($F1 \geq 0.85$) was generally achieved for lakes of above 0.028 km² across the study period, whilst for complimentary data provided by Sentinel-1, a larger size threshold of 0.084 km² was required to reach the same classification performance ($F1 \geq 0.85$), indicating lower robustness for smaller lakes in the SAR-derived dataset. Although the overall elevation distributions of both datasets were similar (median elevations ~5,020–5,060 m), lower-F1 lakes did tend to occur at slightly higher elevations and were generally smaller in area.

However, the multiple linear regression showed that lake area was the dominant control on F1 score for both Sentinel-1 and Sentinel-2. For Sentinel-2, lake area alone explained 42% of F1 variability ($R^2 = 0.42$; $\beta = 0.19$; $p < 0.001$), with a strong positive significant relationship whereby a 10-fold increase in lake area was associated with an increase in F1 score by ~0.19. The addition of elevation provided little improvement to the model although it did have a weak negative but significant influence ($\beta = -2.84 \times 10^{-5}$; $p = 0.02$). Sentinel-1 showed a similar positive relationship between F1 and lake area ($R^2 = 0.24$; $\beta = 0.19$; $p < 0.001$), however lake area explained less of the variance in F1 when compared to optical, indicating lower overall predictability of SAR classifications. For elevation, this had no significant independent effect on Sentinel-1 performance ($\beta = 2.84 \times 10^{-5}$; $p = 0.33$). Overall, Sentinel-1 was associated with lower and more variable F1 scores than Sentinel-2, consistent with the lower robustness of the SAR-derived dataset, particularly for smaller and more geometrically complex lakes.’

Sect 5.3.2:

5.3.2 Recommended use and detection limits

The dataset produced here provides a consistent and reproducible inventory of glacial lakes across the Nepal-transboundary region across the eight-year study period, making it well suited to regional-scale assessments of

lake distribution, presence/absence, and broader interannual change. As with any regional-scale inventory, data confidence varies according to lake size and sensor type. Although a minimum mapping threshold of 0.001 km² was applied in this study, classification performance remains largely size dependent. For Sentinel-2, robust performance ($F1 \geq 0.85$) was generally achieved for lakes of above 0.028 km², whilst for complimentary data provided by Sentinel-1, a larger size threshold of 0.084 km² was required to reach the same classification performance ($F1 \geq 0.85$). A multiple linear regression model further showed that lake area was a dominant control on F1 score for both sensors, whilst elevation exerted a very small secondary influence. For Sentinel-2, the effect was weakly negative and statistically significant ($p = 0.02$), but of negligible magnitude, whereas for Sentinel-1 this was not significant. Together, these results indicate that reduced performance in small, often high-elevation lakes is driven primarily by lake size and the difficulty of complete delineation, rather than elevation itself acting as a strong independent control.

That said, small, irregular and high-elevation lakes do remain particularly challenging due to increased mixed pixel boundaries of water, snow and ice, combined with steep terrain and seasonal partial freezing (Kumar and Vijay, 2026; Qayyum et al., 2020; Watson et al., 2018). This likely explains the slightly lower agreement observed when lake comparisons included the Kumar et al. (2025) inventory, which contained a greater proportion of smaller lakes near the minimum mapping threshold (0.001 km²). Additionally, some smaller lakes are highly ephemeral (e.g., supraglacial lakes) and may partially drain or disappear during the compositing period. In this case, while it would appear as a false negative when compared to Kumar's dataset, it is in fact a true negative, as the lakes were absent at the time of observation. In this context, higher-resolution imagery such as PlanetScope may support improved delineation for small or irregular lakes by resolving these mixed-pixel edge effects (Xu et al., 2024). However, this capability relies on quota-limited free research-programme data access, or paid access to the commercial dataset (<https://www.planet.com/industries/education-and-research/>) and may be most effectively applied to targeted training data or validation.

In terms of sensor specifics, the two sensors provide strengths for glacial lake monitoring. Sentinel-2 is shown to be better suited to the accurate delineation of individual lake boundaries, including smaller lakes, and should therefore be considered the primary dataset for more detailed and complete lake mapping. Sentinel-1 provides a valuable complimentary perspective by offering more consistent, all-weather observations, assisting with supplementing optical data gaps (i.e., the capture of lakes during monsoon or cloudy periods) and improve visibility of snow-or-ice covered lakes (Fig. S4; Fig. S5). It is noted, however, that these Sentinel-1 delineations are more prone to fragmented or irregular lake outlines, particularly for smaller lakes, likely reflecting known SAR challenges including speckle noise, look direction, incidence angle and backscatter variability over water and rugged terrain (Khan et al., 2025; Miles et al., 2017). At the same time, the Sentinel-1 dataset provided more temporally consistent lake counts, which is a likely reflection of a combination of factors: (i) the narrower acquisition compositing window meaning lakes were more likely to be captured at a similar time each year; (ii) a greater omission of smaller lakes, reducing year-to-year variability in the seasonal changes of smaller lakes, that are then intermittently captured by Sentinel-2; (iii) the use of median SAR composites which are more likely to exclude small, highly dynamic lakes (Kumar and Vijay, 2026). As such, Sentinel-1 should be interpreted as reflecting a more conservative subset of lake detections, rather than completeness. Finally, the annual Sentinel-1 and Sentinel-2 mosaics were generated from different acquisition windows to balance the observational capabilities and data availability of each sensor, so some minor differences between the two datasets may reflect differences in temporal sampling. Additionally, the Sentinel-1 model was trained using lake outlines derived from optical imagery (Kumar et al., 2025; Zhang et al., 2024) which may introduce some minor boundary mismatch between training labels and the SAR signal. Given the current lack of SAR-based training data, this approach is a reasonable compromise for Sentinel-1 model development and highlights an important avenue for future model refinement using SAR-based training labels. Beyond the overall strong performance shown of both sensors in this study, and the known limitations, ongoing work will set to further refine the classification models, with additional training and inference planned for the wider Himalayan region.

2- the different compositing windows for Sentinel-1 (July–August) and Sentinel-2 (May–November) introduce a potential sampling bias. Even if justified by cloud cover and image availability, the two sensors are not sampling the same seasonal window, which could influence median lake extent and comparability between sensors. A short

discussion of how much this might affect inter-sensor comparisons would increase confidence in the results. Thank you for your comment. We acknowledge that the annual mosaics for Sentinel-1 and -2 were generated for different time windows and therefore some lake extent variability may occur. These windows were selected to optimise data availability under sensor-specific constraints: Sentinel-1 allows consistent post-monsoon acquisition irrespective of cloud cover, whereas Sentinel-2 requires a broader window to obtain sufficient cloud-free observations in this monsoon-affected region.

Sentinel-1 and -2 datasets were processed independently and are intended to be complementary (rather than comparable). Here, Sentinel-1 data contributes temporally (i.e., during cloudy conditions) when optical observations are limited, whilst Sentinel-2 provides greater spatial lake boundary precision (e.g., smaller lake delineation) during cloud-free conditions.

Some additional text has been added to Sect. 3.1.1, Sect 3.1.2 and Sect. 5.3.2 (see full Sect 5.3.2. above).

We have now added in some additional justifications to the following:

Sect. 3.1.1:

‘A smaller date range was used compared to Sentinel-2 processing (Sect. 3.1.2), as the Sentinel-1 backscatter is not affected by cloud cover, allowing for more images to be available for compositing during the post-Monsoon period when lakes are typically ice-free and near their seasonal maximum extent. Whilst some lake extent variability may occur due to these time window differences per sensor, Sentinel-1 data is intended to be complimentary by contributing temporally when optical observations are limited.’

And Sect. 3.1.2:

‘All available Sentinel-2 images (L1C) were used within the date range of May to November for years 2017 to 2024. This broader date range was used to coincide with the Monsoon season and late-ablation period, when the surface of glacial lakes is typically unfrozen, while also maximising the availability of cloud-free observations and reducing spatial data gaps in this persistently cloudy region.’

3- Sentinel-1 in mountainous terrain is affected by layover, foreshortening, and radar shadow, which can strongly influence backscatter and geometric representation in steep valleys. **It would be helpful to clarify whether SAR visibility constraints were explicitly accounted for, for example by masking radar shadow/layover areas or using terrain-flattened products.** In landslide studies, we have seen that training SAR-based models using inventories digitised from optical imagery can degrade performance if SAR visibility is not considered. There are approaches to compute SAR visibility masks in GEE (e.g., <https://doi.org/10.3390/rs12111867>). This might not be essential here, but **acknowledging this limitation** and potentially considering it in future refinements could strengthen transparency. Related to this, since the training data are derived from optical inventories, it would be useful to briefly comment on **potential cross-sensor discrepancies in geometry or boundary definition** and whether these could influence Sentinel-1 training quality.

Masking of radar shadow and layover areas was performed as part of the processing and we have now added this text. Example areas of masking are visible in (e.g. Fig. S4).

Under Sect. 3.1.1 we have modified the text to read:

‘Sentinel-1 Ground Range Detected (GRD) images (2017–2024) were processed to analysis ready data format following the framework of Mullissa et al. (2021) in GEE, which included speckle filtering, radiometric terrain normalisation, border noise correction, and masking of radar shadow and layover areas (e.g. Fig. S4).’

We agree that there will be some discrepancies between the optical-derived training data and the SAR data, which could reduce the quality of the Sentinel-1 model training. However, it is not possible to quantify this without SAR-specific training data, which to our knowledge is not available. Since the model learns generalised patterns rather than exact pixel-level boundaries, we expect the overall impact on Sentinel-1 training quality to be limited.

We have modified the following text under 3.2 where we introduce the training data:

‘These data were merged, incorporating all lakes from Zhang et al. (2024a), and then supplemented with any additional lakes from Kumar et al. (2025), which were typically smaller supraglacial lakes that were not present in the Zhang et al. (2024a) data. The lake outlines were used to generate training data (512-pixel image chips)

with the corresponding 2020 Sentinel-1 and -2 image composites. There was no systematic coregistration offset between the lake outlines and the imagery we used for training. However, local shifts may occur, particularly in Sentinel-1 data, since the lake outlines were derived from optical imagery. Nonetheless, since the models learn generalised patterns rather than exact pixel-level boundaries, we expect the overall impact to be limited.'

4- The reliance on ArcGIS Pro for model training and deployment may pose practical limitations for some users, particularly given the strong open-data framing of the study. Since a Python file and trained model weights are provided, it would be helpful to clarify how portable these resources are outside the ArcGIS ecosystem. For example, can the trained DeepLabV3 model be readily deployed in standard open-source environments (e.g., PyTorch/TensorFlow workflows), or does it require ArcGIS-specific dependencies?

Our models can be called through ArcGIS Pro or ArcGIS API for Python, but cannot be directly loaded into a fully open source PyTorch workflow. Although all data derived from the models is open, we acknowledge model access is a potential limitation for users wishing to modifying the underlying weights or retrain. We were unable to decouple our models from ArcGIS in this case. We have modified the text under 'Code and data availability'.

'Deep learning models and the GLO glacial lake dataset presented in this manuscript are hosted on the Zenodo data repository at <https://doi.org/10.5281/zenodo.17802334> (Rawlins et al., 2025). Our trained deep learning models rely on ArcGIS for deployment.'

5 – personal curiosity. Can you comment if you had any false positives and in which occasions? Deploying over such large areas is quite challenging.

Thank you for your interest. Yes, false positives (and negatives) were present in both Sentinel-1 and Sentinel-2 inventories, although they generally represent a small proportion of lake-related pixels overall. For Sentinel-2, false positives (FP; i.e., lakes mapped by our deep learning model and not in reference) were generally associated with more smaller lakes that were not in the reference datasets, accounting for 9.8% of lake pixel counts. For false negatives (FN: i.e., lakes/pixels not mapped by our deep learning but present in reference), our deep learning better tracked glacial lake outlines, particularly for larger lakes, where reference data may have over-captured or over-generalised such boundaries (hence FN in our data). Also some lakes which had non-distinct boundaries due to snow, ice cover or shadow were also fully or partially labelled FN, but these were typically smaller lakes. Generally, smaller lakes are more ephemeral and so may have partially or fully drained in our classification, therefore appearing as a false negative (not present) – this is acknowledged in Sect. 5.1. FN equated to 7.2% of lake pixel counts.

For Sentinel-1, again there was good overall agreement, albeit slightly less than Sentinel-2. For FP, our deep learning captured lakes which were partially ice or snow covered were captured more frequently (see Fig. S4), which were not fully captured (if at all) in optical-based reference datasets – also see Fig.(c-d) and (g-h) below. FP accounted for 8.7% of total captured lake pixels. For FN, as discussed in Sect.5.3.2, lakes which had poorer F1 scores and were maybe not captured were smaller in size, surrounded by more complex terrain or be ephemeral in nature (e.g., in particular, supraglacial lakes). FN accounted for 21.7% of total lake pixels, a much larger percentage than Sentinel-2. This therefore reflects our suggestions of using preferential use of Sentinel-2 as the primary dataset, but complimented with data from Sentinel-1, which may have captured some of the more difficult-to-optically-observe lakes. Some examples of TP, FP and FN are now also given in Figure S5 (see below).

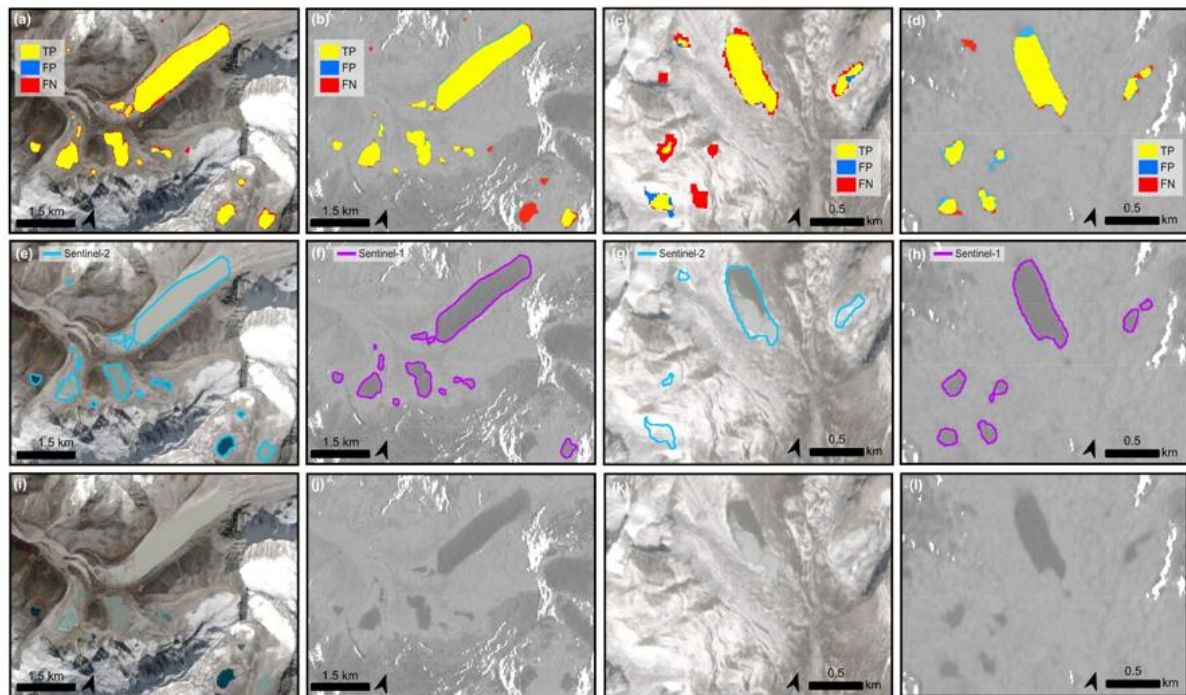


Figure S5: Examples of deep learning classification performance relative to reference inventories for Sentinel-2 and Sentinel-1 (2020) and subsequent lake delineations overlain on Sentinel-2 RGB and Sentinel-1 SAR training imagery. (a-d) True positives (TP), false positives (FP), and false negatives (FN), with left-hand pair (a,b) showing better performance in Sentinel-2, whereas right-hand pair (c,d) showing better performance in Sentinel-1 where snow and ice are more prevalent; (e-h) Corresponding model lake outlines overlain on 2020 training imagery; (i-l) corresponding imagery only.

PDF comments:

[Table 2 – not sure the format adds useful info here](#)

Whilst we appreciate this comment, we believe that including the data format for each variable ensures clarity in the dataset structure and supports the open, reproducible and interpretable use of the dataset across different platforms.

[Line 198 – Maybe polynomial could reveal nonlinear trends here.](#)

We agree that non-linear trends will be apparent for some glacial lakes; however, these are generally apparent on multi-decadal timescales (e.g. Haritashya et al., 2018). Our primary goal was to estimate annual rates of change, whilst accounting for outliers. Applying polynomials to ~8 data points could potentially introduce false trends or spurious reversals of lake area change at the end of the timeseries, whilst also making it difficult to estimate rates of change. We therefore omit polynomials in this analysis but acknowledge the benefit of accounting for non-linear trends as our dataset extends.

[Line 213 – How do you deal with this if for example your median includes such changes? What could be the effect of this?](#)

Thank you for your comment. Median compositing can smooth those short-term changes occurring within the compositing period, therefore expansion, drainage or small shifts in lake position may be underrepresented or omitted (particularly for lakes such as those supraglacial in origin, which are typically more dynamic). This may lead to some reduced detection of lakes or the potential for slight boundary mismatches when compared with other inventories. However, it is important to note that often regional inventories (including our Nepal-transboundary here and the validated inventories we use) are derived from composite imagery and are likely to represent the seasonal state of a lake rather than its short-lived minimum/maximum state over single date/s.

Additionally, as we are only using a single composited year for comparison against the two external inventories, any temporal mismatches are constrained to that year. We believe this median compositing method remains appropriate for regional-scale lake assessments (and for further wider-scale Himalayan inventories).

Line 221 – Maybe adding IoU would be nice

Whilst IoU values are provided in Table S2 and Table S3 in the Supplementary Information, we agree that its inclusion in the main body of text is a valuable addition. These values have now been added into Sect. 4.1.1 and Sect. 4.1.2 for both Sentinel-1 and -2. See added text below.

Sect. 4.1.1

‘First, comparisons with Zhang et al. (2024a) found good agreement in detections between the datasets, resulting in F1 scores of 0.82 for Sentinel-1 and 0.87 for Sentinel-2 (Table S2), with corresponding IoU values of 0.70 and 0.78, respectively.’

Sect. 4.1.2

‘When compared against the combined Zhang et al. (2024a) and Kumar et al. (2025) inventories the F1 scores were slightly lower, with 0.79 and 0.85 for Sentinel-1 and -2 respectively, with corresponding IoU values of 0.66 and 0.74. Again, these results demonstrate good spatial agreement across datasets of differing sensors.’

Line 310 – blank

We could not see this sticky note unfortunately.

Line 325 – Can you be more specific (differ slightly in temporal trends)

We have now amended the text to the following:

‘Collectively the two lake datasets derived from SAR and optical Sentinel sensors (respectively) show broadly comparable spatial patterns across the Nepal-transboundary but differ slightly in their interannual detection behaviour temporal trends likely due to sensor-specific characteristics. Sentinel-2 captured 23% more lakes over the time period with a greater number of unique lakes and year-to-year variability, whilst Sentinel-1 provided more consistent annual detection lake counts with lower year-to-year variability.’

Also, we have added further interpretation of why there is differ in temporal trends in the new Sect. 5.3.2. Text as follows:

‘Sentinel-1 derived lakes provide valuable imaging through all-weather conditions, assisting with supplementing data gaps that may be left by optical images (i.e., the capture of lakes during monsoon or cloudy periods) and even the capture of snow-covered lakes which are omitted in Sentinel-2 (Fig. S4). It is noted, however, that these Sentinel-1 delineations are more prone to fragmented or irregular lake outlines, particularly for smaller lakes, likely reflecting known SAR challenges including speckle noise, look direction, incidence angle and backscatter variability over water and rugged terrain (Khan et al., 2025; Miles et al., 2017). At the same time, the Sentinel-1 dataset does provide more temporally consistent counts, which is a likely reflection of a combination of factors: (i) the narrower acquisition compositing window meaning lakes were more likely to be captured at a similar time each year; (ii) a greater omission of smaller lakes, reducing year-to-year variability in the seasonal changes of these smaller lakes, that are then intermittently captured by Sentinel-2; (iii) the use of median SAR composites which are more likely to exclude small, highly dynamic lakes (Kumar and Vijay, 2026). As such, this temporal variability reflected for Sentinel-1 should be interpreted as reflecting a more conservative subset of lake detections, rather than completeness.’

Line 326 – This is interesting. S1 should be great in detecting water. Do you have any thoughts on why? See which one you miss is terms of size might help seeing whether size matters here. Otherwise, it'd be interested to see whether this is due to geometric distortions (e.g., shadowing)

Thank you for your comment – we agree, in principle, that Sentinel-1 SAR should be effective for water detection. However, in our study the main limitation is not the detection of open water itself, but the reliable detection and delineation of small, irregular or topographically complex glacial lakes because of steep

Himalayan terrain. Our validation indicates that size is a dominating factor, which is now backed up by further robust performance analysis which shows that Sentinel-1 requires a larger lake-size threshold than Sentinel-2 to achieve robust classification performance ($F1 \geq 0.85$).

Line 453 - I'd just say performance

Changed to performance.

Line 474 – what would this be in this case (minimum mapping threshold)?

Here we are referring to our minimum mapping threshold (0.001 km^2), with the Kumar (2025) dataset containing a greater proportion of small lakes that are close to this threshold. The sentence has been restructured for clarity.

‘Notably, when including the Kumar et al. (2025) inventory for our classification comparison, overall F1 and IoU scores slightly decreased for both sensors, including Sentinel-2, relative to comparisons using the Zhang et al. (2024a) inventory alone. This reduction is likely due to the Kumar inventory containing a greater proportion of more smaller lakes near our the minimum mapping threshold (0.001 km^2), which are inherently more difficult to detect and that were less accurately classified due to spatial resolution constraints and mixed pixel effects (e.g. Fig. 5).’

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