

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 O2 regions (Fig. S1a).

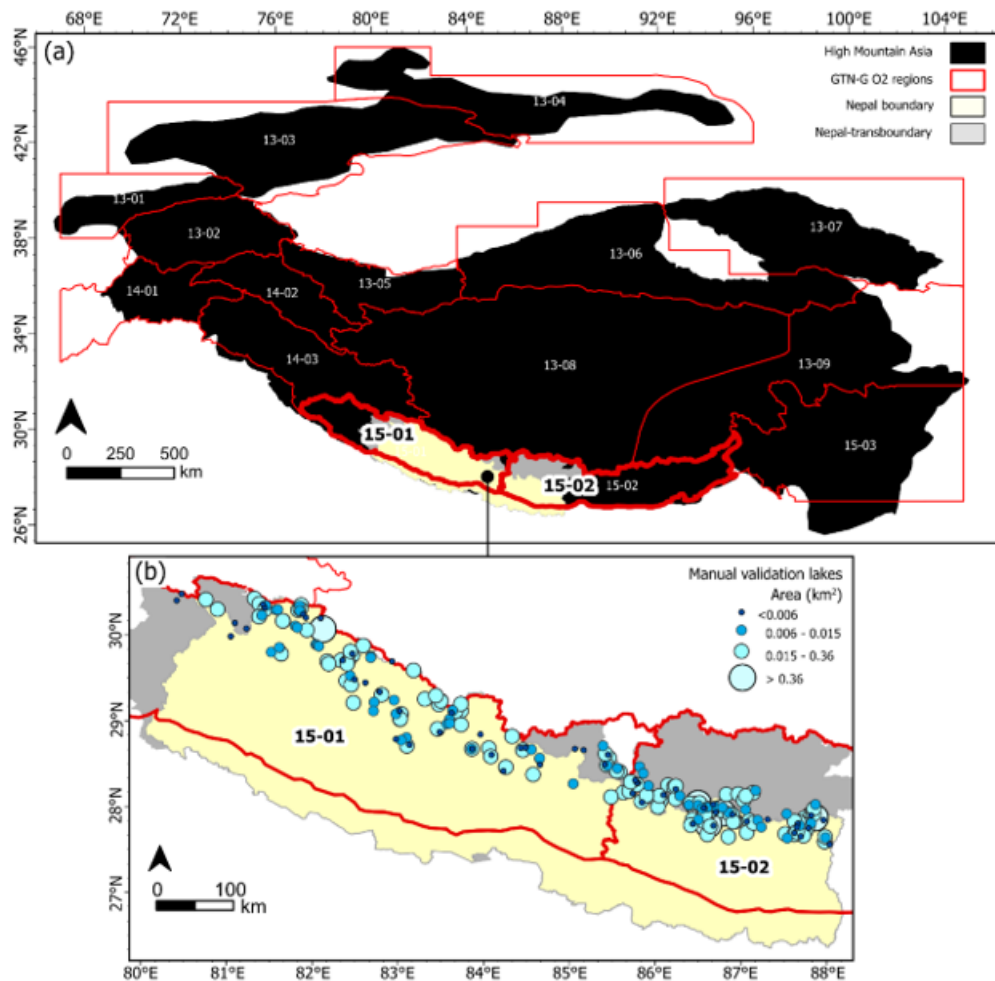


Figure S1: (a) The Global Terrestrial Network for Glaciers (GTN-G) O2-regions for High Mountain Asia (HMA; GTN-G, 2023). The Nepal-transboundary glacial lake dataset spans the O2-regions of 15-01 and 15-02 (Central Himalayas) with a 200 m overlap into 13-08. HMA outline from Bolch et al. (2019); (b) 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.’

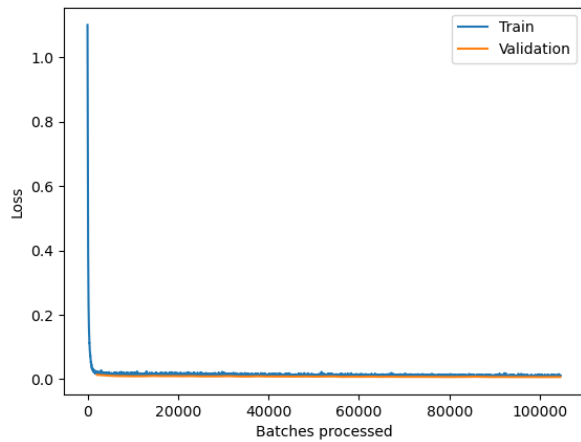
L153ff: Justify in more depth why you chose DeepLabV3 as deep learning model. E.g. did other studies come to the conclusion that this model works best? Maybe give the reader a bit more in-depth information about DL methods that have been used for lake mapping and how well they performed (e.g. by extending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

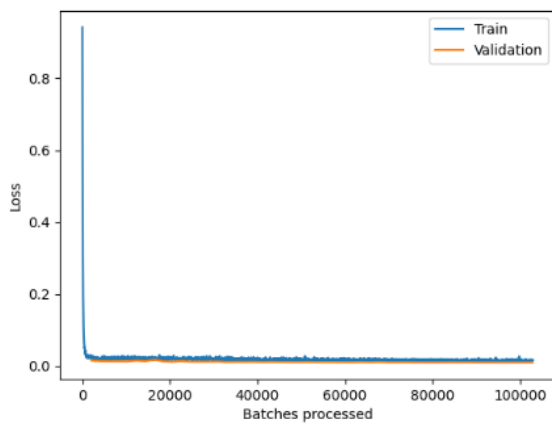
‘Deep learning models such as U-Net, originally designed for biomedical image segmentation (Ronneberger et al., 2015), or DeepLabV3 for semantic segmentation (Chen et al., 2017), are increasingly used for a broad range of geoscience classification tasks. For glacial lake mapping, DeepLabV3 is already 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 $\text{std} > 50$ 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, obscuration 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.

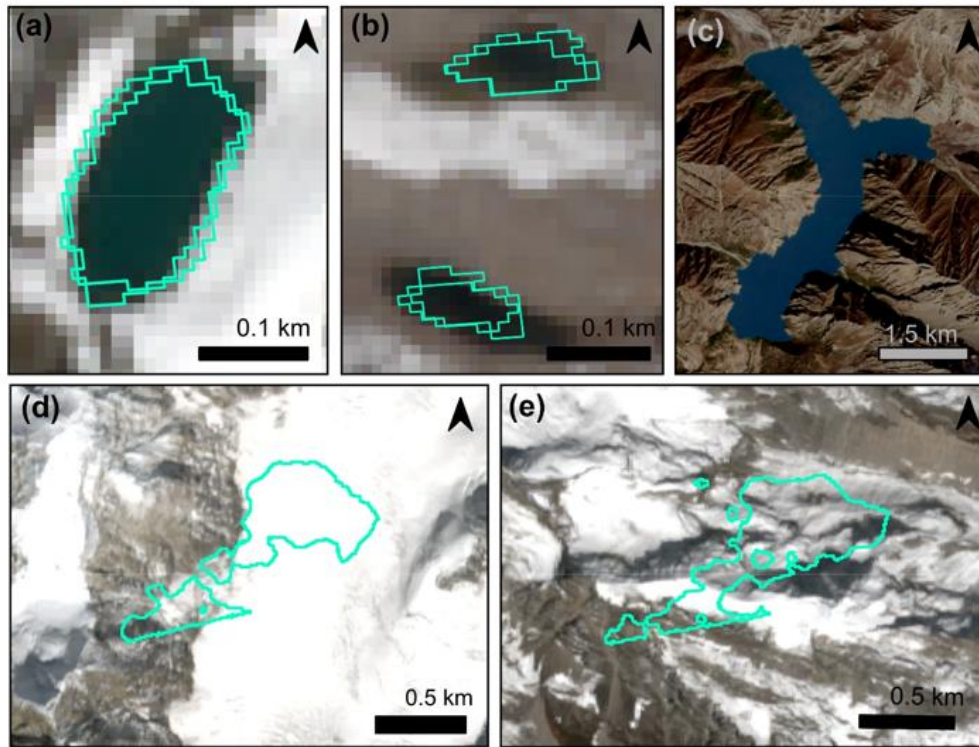


Figure S2: Examples of lake detections removed from the glacial lake dataset. Both (a) and (b) show glacial lakes which detected twice due to slight spatial offsets between adjacent image tiles. These were identified and removed via repeat GLO_IDs. (c) The Shey Phoksundo landslide lake which was removed 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 = 0.79–0.82) relative to Sentinel-2 (F1 = 0.85–0.87). 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.

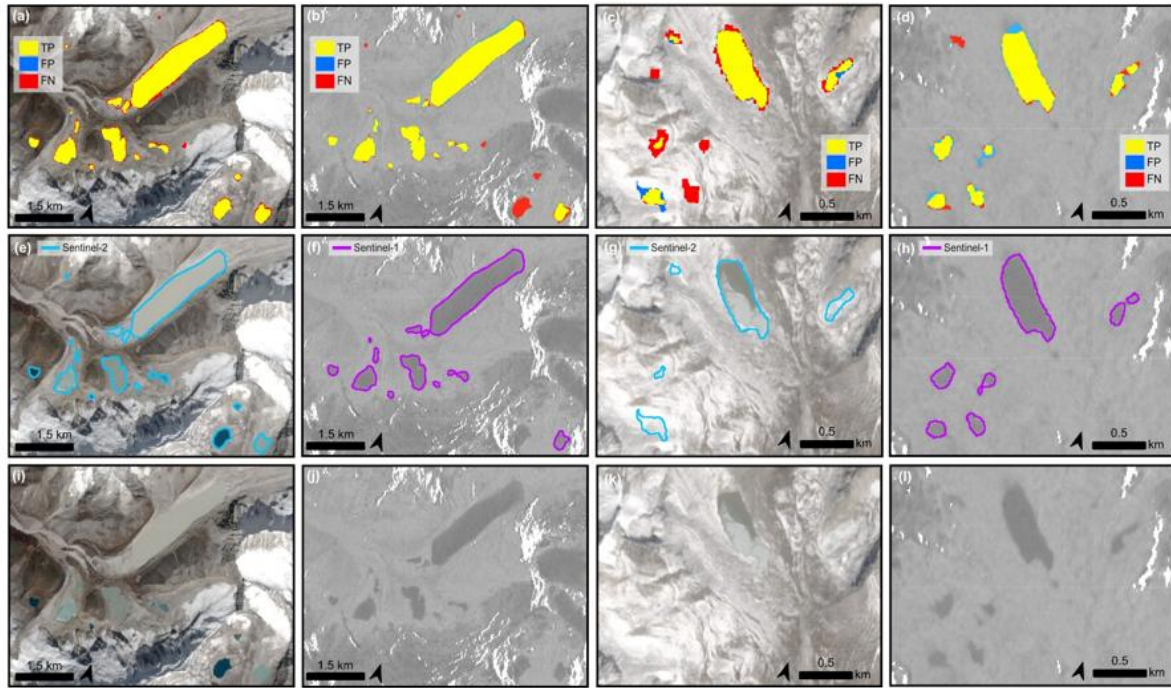


Figure S5: Examples of deep learning classification performance relative to reference inventories for Sentinel-2 and Sentinel-1 (2020) and subsequent lake delineations overlain on Sentinel-2 RGB and Sentinel-1 SAR training imagery. (a-d) True positives (TP), false positives (FP), and false negatives (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 complementary 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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