Mitigating future glacial lake outburst floods in the Himalaya

Xue Wang[a,b]†, Wenfeng Chen[a]†*, Guoqing Zhang[c,a*], Adam Emmer[d,e], Holger Frey[f], Caroline Taylor[g], Christian Huggel[f], Ashim Sattar[h], Guoxiong Zheng[i], Irfan Rashid[j], Jonathan L. Carrivick[k], Georg Veh[l], Simon Allen[f,m], Jakob Steiner[d,n], Duncan Quincey[k], Martin Mergili[d]

[a] *State Key Laboratory of Tibetan Plateau Earth System, Environment and Resources (TPESER), Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing 100101, China*

[b] *University of Chinese Academy of Sciences, Beijing 100049, China*

[c] *Key Laboratory of Biodiversity and Environment on the Qinghai-Tibetan Plateau, Ministry of Education, School of Ecology and Environment, Xizang University, Lhasa 850000, China*

[d] *Institute of Geography and Regional Science, University of Graz, Graz 8010, Austria*

[e] *Department of Physical Geography and Geoecology, Faculty of Science, Charles University, 128 00 Prague 2, Czechia*

[f] *Department of Geography, University of Zurich, Zurich 8057, Switzerland*

[g] *School of Geography, Politics and Sociology, Newcastle University, Newcastle upon Tyne NE1 7RU, UK*

[h] *School of Earth, Ocean and Climate Sciences, IIT Bhubaneswar, Odisha 752050, India*

[i] *College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China*

[j] *Department of Geoinformatics, University of Kashmir, Hazratbal Srinagar 190006, India*

[k] *School of Geography and water@leeds, University of Leeds, Leeds LS2 9JT, UK*

[l] *Institute of Environmental Science and Geography, University of Potsdam, Potsdam-Golm 14476, Germany*

[m] *Institute for Environmental Sciences, University of Geneva, Geneva CH-1211, Switzerland*

[n] *Himalaya University Consortium, Lalitpur 44700, Nepal*

†These authors contributed equally.

*Corresponding author.

Email: guoqing.zhang@itpcas.ac.cn (G.Zhang); chenwf@itpcas.ac.cn (W.Chen)

Abstract

Glacial lake outburst floods (GLOFs) are among the most severe cryospheric hazards in the Himalaya. While previous studies have primarily focused on the characteristics and causes of GLOFs, strategies for mitigating their disaster impacts remain underexplored. This study introduces China's Glacial Lake Management System (GLMS) and evaluates its potential for regional replication in reducing damage caused by GLOFs. We find that while GLOF frequency shows a statistically insignificant decrease from 1990 to 2023, downstream damage has intensified, yet appears relatively mitigated within China across the Himalaya following the implementation of the GLMS. Further hydrodynamic modelling suggests that glacial lakes will continue to expand in the future, with total growth expected to triple relative to the 2000–2020 period. These expansions could increase GLOF exposure by over 27% for high-risk lakes and by more than 40% in regions outside China without targeted interventions. However, implementing GLMS engineering measures could reduce the intensity of future floods by 24%, with even greater reductions outside China–29% compared to 21% within China. Building on China's lake management experience and recognizing the transboundary nature of GLOFs, the comprehensive framework we propose for region-wide glacial lake risk reduction across the Himalaya integrates engineering measures, early warning systems, and community responses. This framework addresses the urgent need for proactive and coordinated mitigation strategies in densely populated high-mountain regions.

Keywords: Himalaya, glacial lake outburst floods (GLOFs), flood intensity, Glacial Lake Management System (GLMS), risk mitigation strategies

1. Introduction

Glacial lake outburst floods (GLOFs) are a significant cryospheric threat in the Himalaya, affecting regions spanning the Hindu Kush, Karakoram, Himalaya, Nyainqêntanglha and Hengduan mountains. These events often cause widespread and catastrophic damage to downstream communities, infrastructure, farmland and ecosystems [1-3]. For example, a recent GLOF event on 8 July 2025 in a China-Nepal transboundary river basin in Gyirong County, Xigazê, Xizang, left 17 people missing and caused significant damage to bridges, hydropower stations, and roads. Previous studies have primarily focused on the characteristics of glacial lake changes, the resulting outburst floods, risk assessments, and the causes of specific GLOF events [3-5]. As glaciers continue to thin and retreat, the glacial lakes they feed are expanding rapidly [6-8]. Some studies suggest that this expansion may increase the risk of GLOF triggers [9, 10]. While some research on past events indicates that glacial lake growth and GLOF triggers are only weakly coupled [11-13]. The increasing availability of optical satellite imagery, particularly with the launch of Landsat-8 and the Sentinel series since 2013, has provided an opportunity to refine our understanding of GLOF trends [12]. However, despite these technological advancements, the development and implementation of effective mitigation strategies remain limited in practice.

GLOF risk is determined by event frequency and magnitude, as well as downstream exposure and vulnerability [9, 14]. With increasing socio-economic activities and expanding infrastructure in high mountain regions, future GLOF exposure is expected to rise, posing a significant challenge for sustainable mountain development [15]. Although engineering interventions such as Tsho Rolpa's siphon system, and community preparedness efforts, like Chungthang's training program [16, 17], GLOFs continue to cause severe downstream damage (Table S1 online). This persistent threat can be attributed to three systemic challenges: (1) inadequate monitoring and early warning systems (EWS) for widely distributed high-risk lakes [18], (2) limited engineering coverage due to financial and logistical constraints in harsh regions (Table S2 online), and (3) delayed emergency response, which hinders the timely dissemination of warnings to affected communities, including those in transboundary areas [19]. Therefore, a reliable and adaptable approach is urgently needed to address these challenges across the Himalaya region.

Since 2019, China has implemented a Glacial Lake Management System (GLMS) to enhance GLOF disaster prevention and mitigation. This system integrates EWS, engineering interventions, and a structured framework for capacity building and responsibility (Fig. 1). A key feature of the GLMS is the assignment of specific personnel for lake management and protection, ensuring coordination across governmental and local levels. This systematic approach facilitates rapid information exchange among stakeholders, including local communities and decision-makers, which improves the effectiveness of disaster response. With several years of successful operation, the GLMS presents a compelling model for exploring how integrated management strategies can address the region's escalating cryospheric challenges.

This study is timely in assessing the effectiveness of China's GLMS and its potential for broader application across the Himalaya. By integrating historical GLOF trends (1990–2023), future projections, and practical mitigation strategies, we assess the GLMS's effectiveness and propose an integrated technical-sociopolitical framework for regional GLOF risk reduction. Combining strategic engineering, community-driven EWS, and transboundary governance, this framework provides scientific insights and actionable guidance for sustainable mountain development and cooperation amid escalating glacier-related geohazards in high-altitude regions.

2. Data and Methods

2.1 GLMS framework

China's GLMS, is a specialized component of China's national River and Lake Chief System, which has been implemented nationwide since 2019 [20]. GLMS is a structured and top-down framework designed to mitigate GLOF risks, through integrated monitoring, engineering interventions, and governance. The system's architecture comprises four key components: inputs, intermediate parameters, functions, and outputs, coordinated across governmental, local, and community levels (Fig. 1).

Inputs: The GLMS relies on near real-time data from optical/SAR satellite imagery (e.g., Landsat-8, Sentinel series, Planet, Gaofen series), UAV-based observations, on-site lake monitoring stations, and community reports. These data sources provide information on lake area, volume, dam stability, and potential triggers (e.g., landslides, avalanches).

Intermediate parameters: Risk assessments integrate input data to prioritize high-risk lakes based on factors such as lake volume, dam integrity, and downstream exposure. These parameters guide decision-making for intervention strategies.

Functions: The GLMS operates through three core functions: (1) EWS: Automated alerts based on monitoring data, disseminated to local authorities and communities via mobile networks and alarms. (2) Engineering interventions: Active measures, such as siphon drainage or spillway construction, and passive defenses, like embankment reinforcement, to reduce lake volumes and flood intensity. (3) Governance and capacity building: Dedicated personnel are assigned to lake management, ensuring coordination between central government, local agencies, and communities. Training programs and emergency drills enhance preparedness.

Outputs: The GLMS aims to reduce GLOF impacts, including minimal damage to infrastructure (e.g., buildings, roads, and bridges), reduced fatalities, and timely evacuations.

The system's architecture facilitates rapid information exchange and decision-making, enabling proactive risk mitigation. For example, monitoring data feeds into risk assessments, which trigger EWS alerts or engineering interventions, with governance ensuring stakeholder coordination. To assess the GLMS's effectiveness, we employed two complementary approaches: (1) a comparative analysis of GLOF damage trends within and outside China before and after GLMS implementation in 2019, and (2) controlled modeling experiments for definitive effectiveness assessment, simulating disaster reduction with and without GLMS engineering measures.

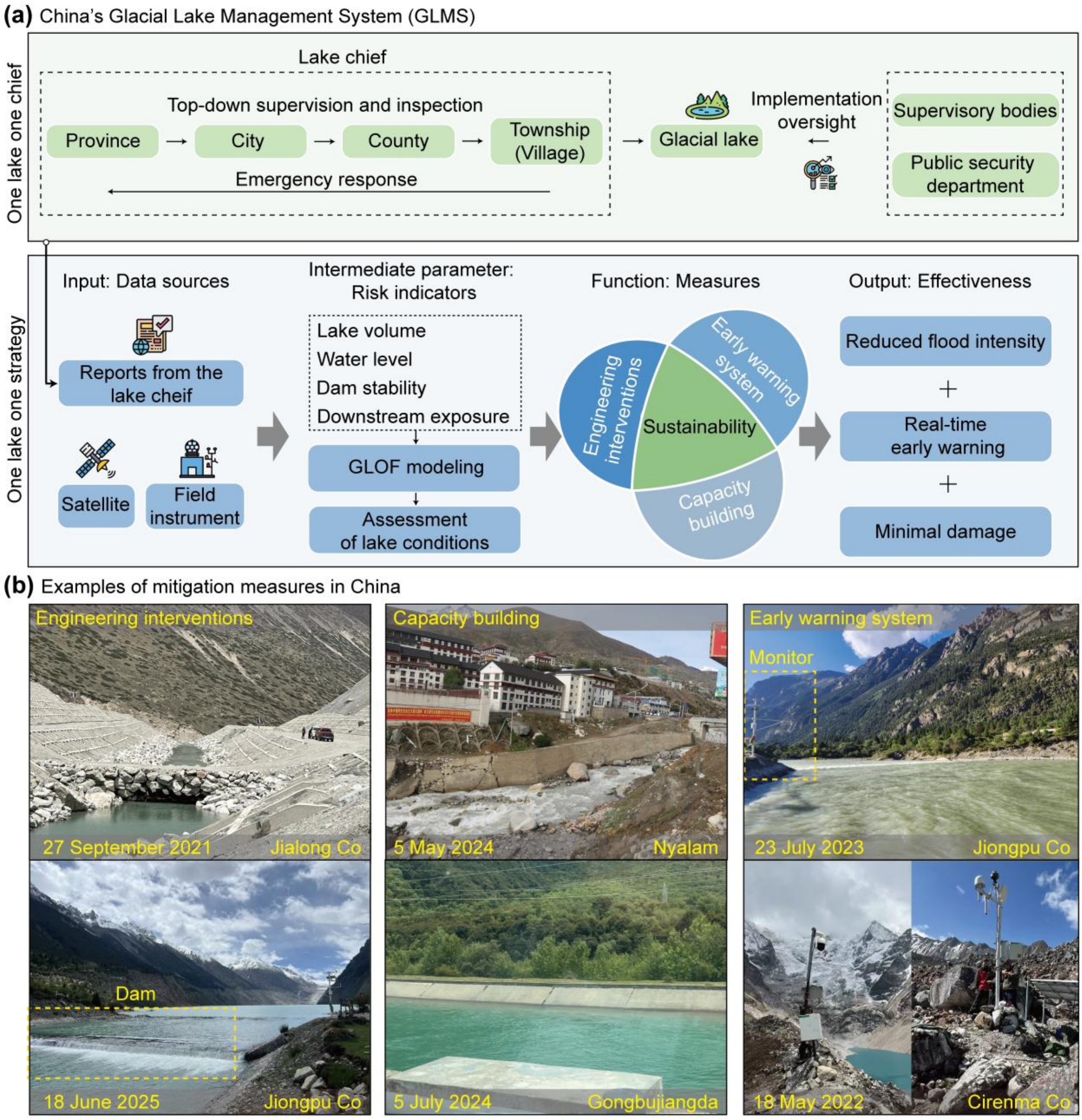

Fig. 1. Architecture of China's GLMS. (a) Coordination of data inputs, risk assessments, functions (monitoring, engineering, governance), and outputs (reduced GLOF impacts) at the governmental and local levels through top-down implementation frameworks. It operates at multiple administrative levels (province, city, county, township, village) ensuring coordinated management. "One Lake, One Chief" and "One Lake, One Strategy" are principles from China's water management system ensuring each glacial lake has dedicated official responsibility for monitoring and safety management, customized risk management plans based on specific lake characteristics (volume, dam stability, downstream exposure) and tailored interventions rather than uniform approaches across all lakes. This creates personalized, accountable glacial lake safety systems with site-specific solutions. (b) Examples of mitigation measures in China. All the lake locations in (b) are marked in Fig. 2.

2.2 Updated historical GLOF inventory and frequency

To assess the trends and impacts of GLOFs across the Himalaya, including the Hindu Kush, Karakoram, Himalaya, Nyainqêntanglha, and Hengduan mountains, we updated the inventory of historical GLOF events. We compiled existing GLOF datasets from peer-reviewed literature, government and institutional reports, news sources, expert interviews, and geomorphic evidence to ensure dataset comprehensiveness and reliability [21-23]. To ensure the accuracy of event identification, we analyzed long-term remote sensing data and cross-validated changes in lake extent with multiple imagery sources (Landsat MSS/TM/OLI and Sentinel-2 imagery with less than 20% cloud cover) for each identified glacial lake. Because sudden reductions in lake surface area can also result from non-GLOF factors such as seasonal drawdown or transient cloud and shadow cover. In addition, a qualitative assessment of the geomorphic conditions before the event was conducted through NASADEM, including the steepness of the slopes around the lake and the integrity of the dam, to diagnose potential GLOF triggers and verify the characteristics after the event. Historical GLOF events from 1990 to 2023 were detected by identifying sudden reductions in lake area and associated geomorphological changes, such as breach formation, deposition of debris fans, and channel erosion [24] (Figs. S1 and S2 online). If the pre- and post-event images were from different years, we assigned the event to the year of the post-event image. To evaluate the impacts of GLOFs, we systematically recorded damage to downstream populations and infrastructure, including roads, bridges, and buildings. Special attention was given to analyzing spatial and temporal variations in GLOF-related damage inside and outside China, particularly after the full implementation of the GLMS in China since 2019.

Assessing long-term trends in GLOF activity is challenging due to inconsistences in historical records. Variations in criteria and methodologies used to identify and catalog GLOFs have led to discrepancies among studies [21, 23, 25]. Additionally, improved satellite data coverage and increased research attention have led to the identification of smaller GLOFs that were previously overlooked [26], potentially biasing frequency analyses [24]. Using the updated GLOF dataset, we reassessed the temporal trends of historical Himalaya GLOFs. Due to the incompleteness of early records, our analysis focused on events occurring after 1990, when research activity became more consistent and comprehensive [26] (Fig. S3a online). To mitigate potential biases introduced by variations in satellite image availability, we employed two independent methods to assess changes in GLOF frequency over time [12].

Method I: Normalization based on image availability: This approach evaluated the regularity of annual GLOF events in lakes with sufficient satellite imagery. We defined "adequate imagery" using the interquartile range (IQR) of time intervals between pre- and post-GLOF images. The standard based on IQR can effectively eliminate the influence of outliers and utilize the statistical properties of IQR to reasonably categories image data availability, ensuring the robustness and reliability of the analysis results [12]. Specifically, we set thresholds of 48 and 240 days for the 25th and 50th percentiles, respectively (Fig. S3b online). Lakes with at least one pair of images separated by 48 days (or 240 days) were classified as having sufficient imagery. To account for differences in image availability, we normalized GLOF frequency by computing the ratio of detected GLOF events to the number of lakes with sufficient imagery per year, for each threshold.

Method II: Standardization at constant image availability: To further control for biases related to image frequency, we used a bootstrap resampling method to assess trends under a fixed number of available images per year. We randomly selected a constant number of images per year (50 and 100 images), recorded the number of GLOF events detected, and fitted a linear trend to estimate changes in event frequency over time (Fig. S3c online). This process was repeated 10,000 times to capture variability in trend estimates.

2.3 GLOF simulations

Our GLOF simulations focused on flood changes before and after engineering measures implementation. We conducted simulations using two complementary models: r.avaflow and HEC-RAS. r.avaflow, an open-source GIS framework, was selected for the Jialong Co case study due to its ability to dynamically simulate complex process chains, including ice avalanches, lake outbursts, and debris flows, with high fidelity in site-specific scenarios (Text S1 online). HEC-RAS was used for region-wide simulations of 43 high-risk proglacial lakes, as future landslide zones, shifting with glacier retreat, are uncertain, and its hydrological modeling ensures comparability across diverse Himalaya terrains (Text S2 online). This dual approach enabled to assess both the detailed effectiveness of GLMS interventions at a single lake and the broader regional implications of mitigation strategies. Jialong Co, a glacial lake in the Poiqu River basin, poses a significant high-risk level if impacted by an ice avalanche. A potential outburst flood could severely affect Nyalam town and downstream areas in Nepal [27]. Following the implementation of the GLMS, local authorities took proactive measures to lower the lake's water level to mitigate this risk (Fig. S4 online). To model the potential evolution and impacts of a GLOF at Jialong Co, we used the open-source GIS simulation framework r.avaflow [28], which dynamically simulates landslide-lake interactions and debris flow hydraulics. The model has previously been applied to simulate complex process chains, such as the 2012 Santa Cruz GLOF involving multiple lakes [29] and the 1962 and 1970 Huascarán landslides [30], demonstrating its capability in simulating process transformations at system boundaries. In this study, we performed simulations for both pre- and post-mitigation conditions, assuming an ice avalanche impact scenario originating from the steep adjacent glacier.

The model setup incorporated several key inputs. The avalanche source was identified as the glacier tongue, which is highly susceptible to collapse due to its crevassed and steep surface. The global glacier ice thickness dataset, which is based on a consensus of five different ice thickness models, was used to calculate the volume of the potentially unstable area [31]. The estimated avalanche volume was approximately 1.9×10^{7} m^3. Terrain data were derived from the global TanDEM-X Digital Elevation Model (DEM), which shows superior performance compared to NASADEM in Jialong Co case study using r.avaflow, was specifically employed for modeling potential GLOF scenarios. Lake bathymetry and volume were obtained from a 2019 uncrewed surface vessel (USV) survey, referencing the WGS 84 UTM zone 45N coordinate system. The estimated lake volumes before and after water level reduction were calculated using Landsat OLI boundary vector data, assuming a constant lake bed, and processed with the surface volume tool in ArcGIS 10.2 [32]. Material properties were defined for the different components of the flow. The initial avalanche was modeled as a two-phase flow, consisting of a solid phase (ice: ρ=900 kg m^{-3}) and a liquid phase (lake water: ρ=1000 kg m^{-3}). The moraine dam was designated as an entrainment zone composed of a solid phase (moraine: ρ=2700 kg m^{-3}) [27]. Entrainment was simulated using a simplified model, where the entrainment rate is proportional to flow momentum and an empirical entrainment coefficient was set $10^{-6.5}$ [28]. However, for the post-mitigation scenario, we assumed that entrainment did not occur, as the dam had been strengthened and sediment deposition into the lake was not considered [27]. Friction parameters were defined based on the nature of the flow. During the initial avalanche stage, the basal friction angle was set to φ = 25°, with an internal friction angle of δ = 10°. For the flow process beyond the moraine, where the flood transforms into a water-saturated debris flow, we adjusted the internal friction angle to δ = 1°, while keeping the basal friction angle at φ = 25° [33]. The total simulation time was set to 1200 seconds, allowing sufficient time for the flood to travel downstream. To assess the potential impacts on downstream areas, we extracted flow characteristics such as flow depth and velocity by defining a cross-section along the flow channel at Nyalam town. This provided insights into the flood behavior and its potential consequences for local infrastructure and communities.

Future GLOF simulations were conducted exclusively for very high-risk glacial lakes [15]. Only proglacial lakes were modeled due to their susceptibility to external influences, and lakes with a projected future area smaller than 0.1 km² were omitted to minimize uncertainties. Given the impracticality of investigating all possible lake failure triggers in the field, we assumed a generalized scenario. To model GLOFs, the potential drainage volume of each lake (V_d) was determined based on its total volume (V_0) using the empirical relationship [9]:

$$V_d = 1.14{V_0}^{0.74} \tag{1}$$

Peak discharge (Q) was estimated using a well-established nonlinear relationship derived from statistical data [34]:

$$Q = 0.045{V_d}^{0.66} \tag{2}$$

Based on the estimated drainage volume and peak discharge, a hydrological break curve was obtained, assuming that drainage volume changes linearly over time [35]. Previous studies have shown that this assumption does not significantly impact flood evolution [36-38]. The length of the flood impact track (L) was derived from the drainage volume using the empirical equation [11]:

$$L = 12.61{V_d}^{0.38} \tag{3}$$

We employed freely available NASADEM (30 m) to perform extensive GLOF simulations in the complex terrain of the Himalaya due to the better consistency compared to global TanDEM-X DEM, which exhibits anomalous values in many regions [39]. Model parameter selection was guided by a preliminary sensitivity analysis, setting the minimum computational unit to 30 m, the Manning coefficient to 0.05, and ensuring a simulation runtime exceeding 10 hours to allow sufficient flood propagation. The HEC-RAS model was used to compute the inundation area, maximum depth, and velocity, as it has been validated in numerous studies.

To quantify GLOF intensity, we defined an indicator (H) following Maranzoni et al. [40]:

$$H = hv \tag{4}$$

where h is the maximum flood depth at a given location and v is the maximum velocity. Floods were classified into four intensity levels—low, medium, high, and extreme—based on velocity and depth. Given the elevated flood risks in the Himalaya region with its steep valleys and high relief, an intensity threshold of 10 was set for the "extreme" flood class.

2.4 Predicting the future development of glacial lakes and validation

Proglacial lakes form adjacent to glacier termini, primarily as moraine-dammed lakes, blocked by sediment and debris in deglaciated areas, or ice-dammed lakes, blocked by ice in actively glaciated regions. In the Himalaya, moraine-dammed proglacial lakes predominate, posing the highest GLOF risk and persisting in retreating glacial landscapes [23, 32]. Given the projected increase in these lakes due to climate-driven glacier retreat, our study focuses on moraine-dammed proglacial lakes to predict their future development and inform hazard mitigation [15, 41]. Our proglacial lake prediction model consists of two main components: an ice thickness module and a subglacial depression module. The model is implemented in MATLAB, with the ice thickness module developed in this study and the depression module adapted from a previous study [42]. The model iterates between estimating subglacial depressions and constraining the ice thickness until the parameters converge (Figs. S5 and S6 online).

Accurate estimation of subglacial depressions relies on the precise modeling of present ice thickness and bedrock topography [43]. In this study, we re-implemented the mass conservation model by Huss and Farinotti [44] to estimate ice thickness for all lake-terminating glaciers, as this approach has demonstrated robustness against errors in input datasets such as DEMs and glacier boundaries [45] (Text S3 online). The model inputs include NASADEM and modified Randolph Glacier Inventory (RGI) 6.0 data. We utilized NASADEM due to its high temporal consistency, representing glacier topography in 2000. By coupling this with corresponding glacier boundaries from the same period, we can accurately derive glacier thickness and identify subglacial depressions (potential future lake formation sites) while avoiding thickness modeling errors that could arise from temporal inconsistencies between glacier boundaries and topographic data [44]. While most parameters remain consistent with the original model [44], we modified the approach for determining the sliding Fsi and correction parameters to better account for variations in glacier dynamics.

One key modification involves incorporating the influence of meltwater lubrication at the terminus of lake-terminating glaciers, which enhances basal sliding. In the original model, the sliding factor is empirically derived based on glacier size and remains constant across the entire glacier. Here, we introduced a more localized approach by defining the sliding parameter for each 10-m elevation band within the model. Specifically, we assumed that the basal sliding ratio of glacier ice in direct contact with a glacial lake should not exceed 0.9, and we applied an inverse tangent activation function to gradually reduce the sliding ratio to 0.2 near the equilibrium line (Equation 1). This ensures a higher sliding ratio near the lake, with a rapid decrease as the distance from the lake increases. The accumulation area ratio was set to 0.44 for the entire Himalaya, following the findings of Miles et al. [46].

Despite these refinements, the sliding ratio remains an empirical parameter, and the actual conditions may vary across different glaciers. To improve model reliability, we introduced three additional constraints to refine and correct predictions. These constraints help ensure that the estimated ice thickness and subglacial depressions align with observed glacier behavior and known physical processes.

$$fsl(h_{(normalizing)}) = 1 - (e^{h_n} + e^{-h_n})/(e^{h_n} + e^{-h_n{}'}) \quad (5)$$

where h_n is a normalizing elevation.

Thickness measurements of glacial contact lakes are difficult and limited by terminus topography (Fig. S7 online). To refine the accuracy of our model, we applied three key constraints to correct and validate the simulated ice thickness and future lake development. First, we accounted for the discrepancy between the observed elevation change at the glacier terminus and the actual ice thickness. The elevation changes of lake-terminating glacier termini, as derived from remote sensing, only represents the thickness of ice above the water surface (H_{ow}), which is less than the full ice thickness (H_g). To ensure realistic estimates, we required that the simulated glacier thickness in the expanding portion of the glacial lake (2000–2020) exceeded the observed elevation change (d_H) obtained from remote sensing datasets [47]. We validated this elevation change estimates using TanDEM-X CoSSC and NASADEM datasets at Galong Co, achieving a high correlation (R^2=0.85, RMSE=7.8 m) (Fig. S8 online). Since ice thickness models often underestimate thickness near glacier margins due to interpolation effects [48], we introduced a 90% threshold correction, which yielded optimal estimates when compared to in-situ ice thickness measurements.

Second, we constrained the modeled subglacial depression by ensuring that its extent in contact with the proglacial lake was larger than the observed glacial lake expansion from 2000 to 2020. This prevented underestimation of future lake growth by requiring the model to account for real-world trends in lake expansion. Third, we refined the final iteration of the model by minimizing the error between the simulated glacial lake volume growth (2000–2020) and the volume calculated using the area-volume scaling method [32]. This ensured that the modeled lake evolution was consistent with empirical data. By integrating these constraints, we derived the distribution and depth of subglacial depressions connected to proglacial lakes. Combining this information with the observed glacial lake extent in 2020, we determined the projected future extent of each glacial lake under continued deglaciation.

Nine glaciers were selected for model validation as they possess independent geodetic measurements and corresponding lake bathymetry datasets, enabling the calculation of glacier thickness at the terminus. The geodetic method determines glacier thickness changes above the water surface (H_{ow}) by subtracting two or more DEMs. The ice thickness below the water surface corresponds to the depth of the glacial lake (H_{sub}) formed after the glacier retreats. Bathymetric data were collected using an USV during fieldwork from 2017 to 2021. By summing H_{ow} and H_{sub}, we reconstructed glacier thickness for the year 2000 (H_g), assuming minimal sediment infill over this period. Two of the examined glacial lakes, Ranzeria Co and Jiweng Co, experienced outburst events in 2013 and 2021, causing water level drops of ~20.2 m and ~25.8 m, respectively [49]. Since bathymetry data were measured post-outburst, these drops were added to the measured depths to estimate pre-outburst lake depths.

Although our model predicts the maximum possible extent of future glacial lakes, factors such as ice thickness uncertainties, sediment accumulation, and outlet variations may prevent lakes from reaching these extents. Increasing glacier thickness deepens subglacial depressions, sometimes merging isolated depressions and expanding projected lake areas. Remote sensing data from 2000 to 2020 were used to validate the modeled extents of subglacial depressions. Underestimated ice thickness resulted in smaller depressions, making this validation approach viable, whereas overestimated ice thickness posed challenges. To assess the sensitivity of ice thickness on lake projections, we scaled glacier thickness in 10% increments from 50% to 150% (Fig. S9 online). Using these thickness variations, we computed corresponding changes in lake extent and volume and estimated the sensitivity.

3. Results

3.1. Initial performance of GLMS implementation

To evaluate the effectiveness of the GLMS, we compare downstream damage caused by GLOFs within China to those outside China across the Himalaya. Both regions have comparable numbers of proglacial lakes, historical GLOFs, and future high-risk lakes [15, 32], which facilitates a meaningful comparative analysis. We updated and validated previous regional GLOF inventories [9, 21-23], excluding 62 cases with no confirmed and clear evidence of an outburst (Fig. S10 online, Table S3 online). Considering all types of dams, including moraine, ice, and other natural barriers, we compiled a comprehensive GLOF dataset spanning1990 to 2023, consisting of 59 events within China and 93 events outside China (Fig. 2a, Table S1 online). Most events were concentrated in the Central Himalaya and Karakoram, with 92% of GLOF events in the Central Himalaya originating from moraine-dammed lakes.

To assess temporal trends in GLOF activity, we employed two independent methods to account for biases introduced by variations in image availability (Fig. 2b-c). First, we analyzed the annual number of GLOFs and the proportion of lakes that experienced GLOFs each year. Both indicators showed statistically insignificant decrease trends over time, respectively, with the best-fit linear trends close to zero. Second, we applied a bootstrap method to further correct for potential biases related to image availability [12], which similarly showed no increasing trend in GLOF frequency over time. Separate analyses for regions within China and outside China yielded consistent findings, with no significant temporal changes in event occurrence (Fig. 2b-c), despite the ongoing acceleration of glacier thinning and retreat, and the continued expansion of both the number and area of glacial lakes (Fig. S11 online).

Although the frequency of GLOFs has remained stable, the resulting damage to downstream communities, such as buildings, bridges, roads, and human lives, has intensified, primarily due to rising exposure and vulnerability (Fig. 2d-e). Prior to 2005, only minor damage was reported in association with 10 GLOFs. However, as downstream populations have grown and infrastructure has expanded, exposure to these events has increased, leading to a corresponding rise in their impacts. After 2005, 31 GLOFs recorded in China, six GLOFs in China caused significant damage, including the destruction of at least 88 buildings, damage to 71.4 km of roads, destruction of 30 bridges, and two fatalities. This trend is even more pronounced in regions outside China. Of the 51 GLOFs recorded, 15 caused damage to at least 26,721 buildings, nine affected 32.5 km of roads, 14 damaged 65 bridges, and five events resulted in 6149 fatalities.

From the implementation of GLMS in 2019 to 2023, four GLOFs have occurred in China (Kyagar lake, Jiweng Co, and two unnamed lakes), with only one causing downstream damage—the 2020 Jiweng Co event. Notably, the village head received advance warning from an upstream villager about the glacial lake burst, enabling downstream villagers to evacuate to higher ground. Despite heavy infrastructure damage, no lives were lost, demonstrating the effectiveness of the EWS incorporating community patrols. Community participation and timely early warning mechanisms, where local managers successfully issued warnings for glacial lake outburst events, demonstrating the advantages of the "One lake, One chief" responsibility system in GLMS. In contrast, of 16 GLOF events occurring outside China after 2019, seven caused damage to over 60 people, 58 bridges, 30 kilometers of roads, and 26,354 buildings, indicating the potential protective benefits of systematic GLOF management systems. Available data suggests positive indications for China's GLMS performance, with reasonable grounds to expect similar systems could improve GLOF risk conditions elsewhere. However, definitive evidence remains limited due to the short observation period since 2019, infrequent GLOF occurrence leading to weak statistical power, and numerous confounding factors including different geological conditions, exposure patterns, and reporting systems across regions [50]. To address these limitations in regional comparisons and provide more conclusive evidence, we conduct controlled modeling experiments at specific glacial lakes in the following analysis, which eliminate confounding factors by maintaining identical environmental conditions while varying only the management interventions.

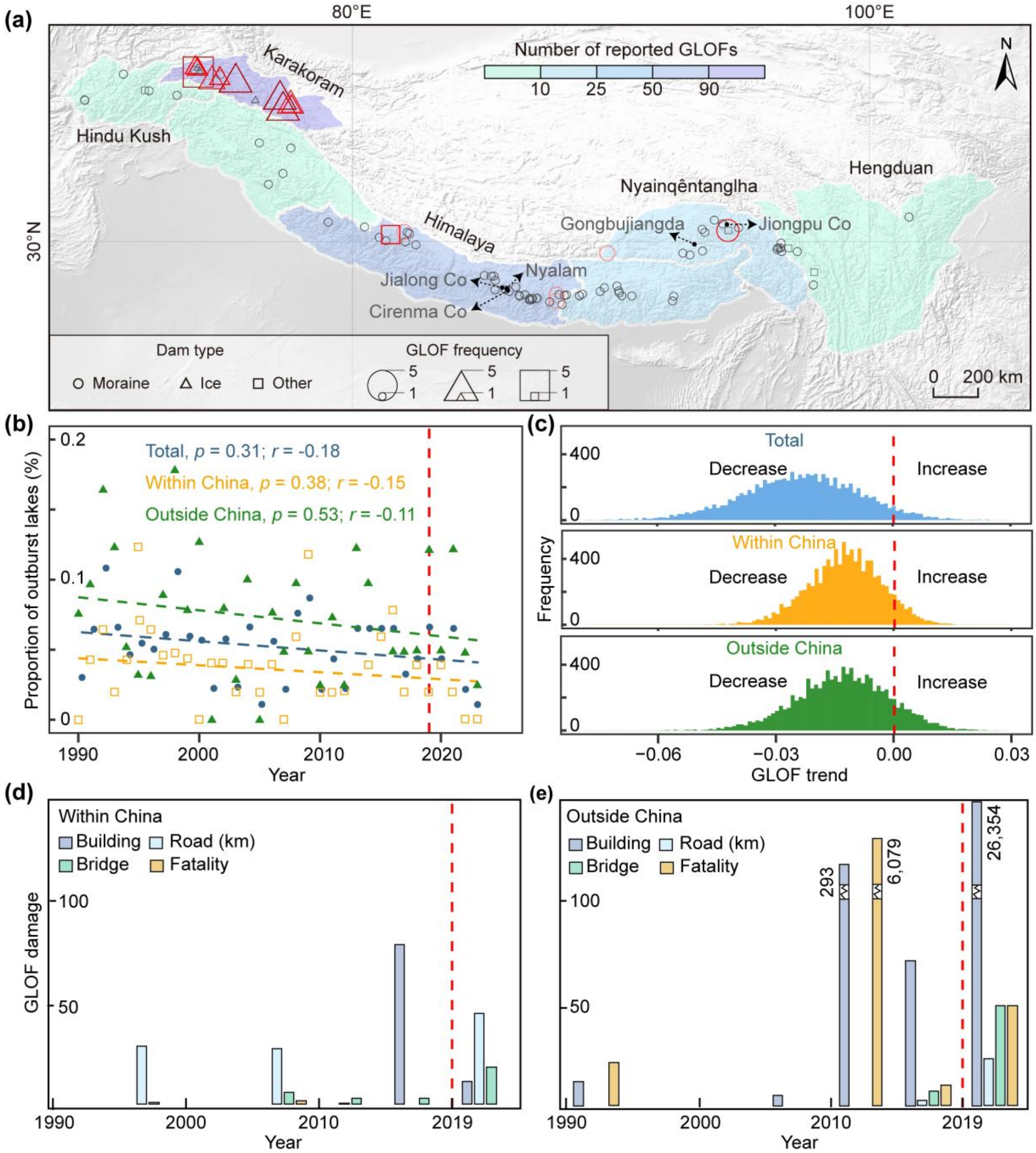

Fig. 2. Historical GLOF trends and damage in the Himalaya. (a) Spatial distribution of historically reported GLOFs within China and outside China across the Himalaya, categorized by dam type. The number of recorded GLOFs in each subregion of the Himalaya is distinguished by varying background fill colors. (b–c) Trends in all recorded GLOFs compared to those occurring within China and outside China. The left panels show the proportion of lakes that burst in a given year, calculated as the ratio of reported GLOF events to the number of lakes with sufficient satellite imagery. The right panels display the distribution of trends over time based on bootstrapping, where 50 satellite images per year were randomly sampled, and event trends were

computed 10,000 times. In all cases, the trend slope remains below zero (x-axis), indicating no increasing trend in GLOF occurrence over time when accounting for satellite image availability. (d–e) Damage to buildings, roads, bridges, and populations caused by GLOFs since 1990 within China and outside China, aggregated over 5-year periods.

3.2. Projected intensification of GLOFs in absence of GLMS

Understanding the future intensity of GLOFs is critical for assessing downstream risks and informing mitigation strategies. To achieve this, we developed a vertically and horizontally constrained ice-thickness inversion model that integrates lake expansion and terminal elevation changes (see Methods, Fig. S12 online). The simulated ice thicknesses for the nine glaciers demonstrated strong agreement with observed values, with correlations ranging from 0.55 to 0.94 and root-mean-square errors (RMSE) between 5.0 and 36.1 m (Fig. S13 online).Our projections indicate that the maximum area of existing proglacial lakes will reach approximately ~377.7 km^2 once glaciers and glacial lakes detach, nearly three times the extent mapped in 2000 (~123.2 km^2) (Fig. 3). The projected increase in lake area and volume is about 251.3 km^2 (+200%) and 11.8 km^3, respectively, compared to their 2000 levels. Potential growth after 2020 is estimated to be approximately 178.4 km^2 and 8.7 km^3, representing 244% and 284%, respectively, of the changes observed from 2000 to 2020 (Fig. 3).

Future glacial lake expansion is expected to vary significantly in both spatial patterns and sizes. The Central Himalaya, Nyainqêntanglha, and Eastern Himalaya will experience the largest increases in lake area, accounting for 38.6%, 24.0%, and 17.6% of the total expansion, respectively. These patterns closely mirror the projected trends in water volume. Most lakes in the 0–0.1 km^2 range (77%, n=641) have limited potential for further expansion (Fig. S14 online). The most significant contributions to lake growth will come from those in the 0.5–2.5 km^2 size range, with approximately half of these lakes projected to grow. In contrast, larger lakes show limited potential for future expansion. Of the 10 lakes larger than 2.5 km^2, five are already constrained by topographic limitations, leaving less than 10% capacity for further growth. Overall, the potential for future glacial lake expansion in the region will be driven by a minority of lakes. Notably, just 25% of lakes will account for 84% of the total area growth and 88% of the total volume increase, highlighting the need for targeted mitigation measures.

Given the projected expansion of glacial lakes and their potential to amplify downstream flood risks, assessing the future intensity of GLOFs from high-risk lakes is crucial for prioritizing mitigation efforts. We modeled future GLOFs for 43 high-risk proglacial lakes (Table S4 online), over half of which (56%) are in the Central Himalaya and 21% in the Eastern Himalaya (Fig. 4). Without additional engineering interventions, their area and water volume are expected to increase by 48% and 43%, respectively. Of these changes, 57% of area growth and 50% of volume growth will occur in China, compared to 37% and 34% outside China. Consequently, future flood intensity, defined as flow depth multiplied by velocity, is projected to rise by over 27%, with increases of 26% in the Central Himalaya and 22% in the Eastern Himalaya. Specifically, GLOF intensity is expected to increase by 21% for 25 lakes within China and by 40% for 18 lakes outside China (Table S5 online). These findings suggest that regions outside China may experience greater increases in GLOF intensity.

3.3. Mitigating future GLOF risk through GLMS implementation

Mitigating future threats is critical to safeguard downstream regions, given the projected rise in GLOF intensity from high-risk lakes. Engineering measures, specifically targeted at GLOFs through China's GLMS, can substantially reduce disaster risks. We simulated the GLOF process for Jialong Co before and after a 20-m water-level reduction (Fig. S4 online). The modeled peak discharge decreased by 50%, from 2×10^4 to 1×10^4 m^3/s, significantly reducing the flood impact on the town of Nyalam. If the same engineering measures applied across all high-risk glacial lakes in the Himalaya could reduce their total area and volume by approximately 25% and 28%, respectively. The Central Himalaya has the highest potential for reduction, with projected decreases of 30% in lake area and 32% in volume compared to lakes without engineering interventions. High-risk lakes inside and outside China could expect reductions of 24% vs. 27% in area and 27% vs. 30% in volume, respectively.

Engineering measures that reduce lake water volumes can significantly decrease potential flood runoff distance, flow intensity, and inundation width along both riverbanks (Fig. 4). Future GLOF inundation areas are projected to be reduced by 20% with engineering measures compared to without them. Implementing the GLMS would significantly decrease GLOF intensity, particularly under extreme conditions, with the magnitude of high and extreme intensity floods dropping by ~24%. Nearly a quarter of lakes would experience a reduction in potential flood intensity exceeding 50% (Table S6 online). Regionally, the estimated reduction is ~18% in the Central Himalaya and ~24% in the Eastern Himalaya. The GLOF intensity of high-risk lakes could be reduced by ~21% inside China and ~29% outside China, highlighting the effectiveness of engineering measures in GLMS in mitigating future GLOF hazards (Fig. 4).

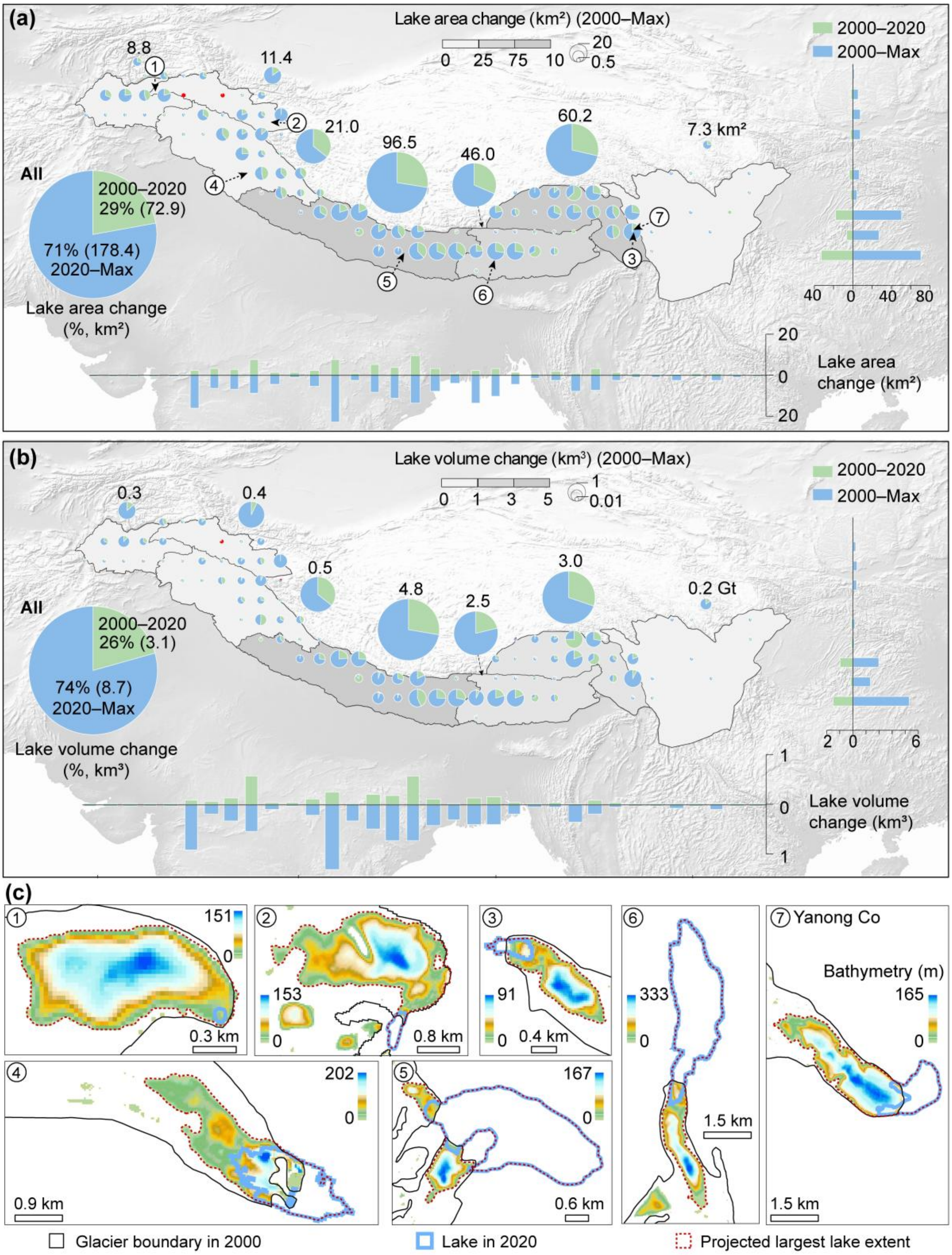

Fig. 3. Future changes in existing glacial lake area and volume. (a) Projected future expansion of existing proglacial lakes, using observed growth from 2000 to 2020 as a baseline. Lake growth trends along longitude and latitude are also shown. (b) Same as a, but illustrating projected changes in glacial lake volume. Both lake area and volume are expected to increase by over 300% compared to the 2000–2020 period, with the most significant growth occurring in the Central Himalaya. (c) Predicted future lake extent and water depths of

maximum lake within each region. Locations are marked with triangular symbols with numbers in (a).

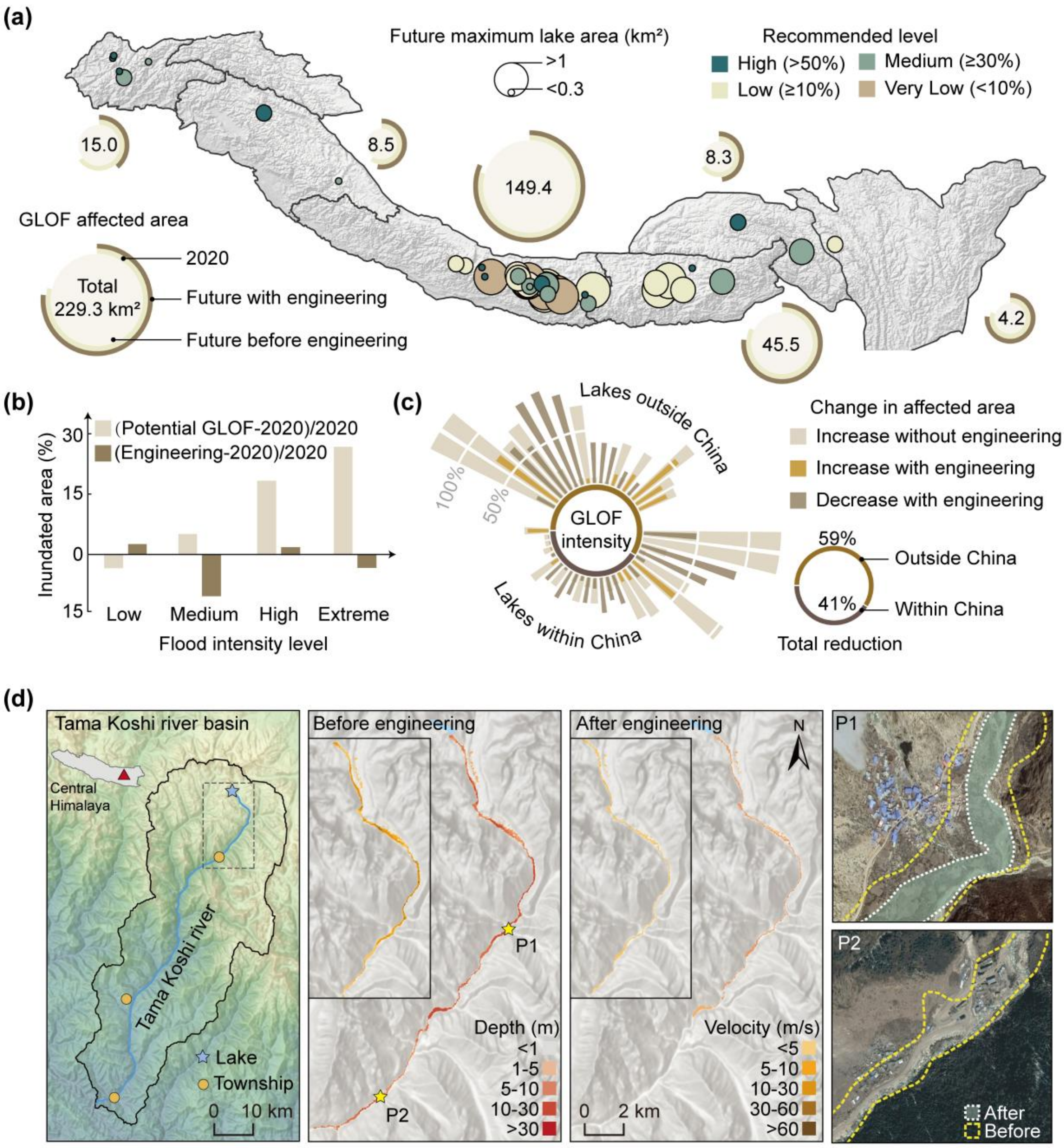

Fig. 4. Damage reduction before and after implementing GLMS engineering measures. (a) Reduction in flood intensity for potentially dangerous glacial lakes in each region, with proposed engineering interventions for each lake. Ten lakes are highly recommended for engineering, as flood intensity was reduced by over 50% with these interventions. (b) Changes in flood inundation area across different intensity levels. The extreme flood inundation area is projected to increase the most in the future but will also experience the greatest reduction after implementing artificial lake level management. (c) Changes in flood intensity from 2020 to the maximum projected extent, comparing scenarios with and without artificial measures. The total reduction in China represents the percentage change in the potentially affected area of lakes within China before and after engineering, relative to the change in the potentially affected area of all lakes. The impact of artificial measures on reducing the risk of potentially dangerous glacial lakes is more significant outside China than within China.

(d) Comparisons of the changes in flood depth, speed and intensity with and without artificial measures. Artificial measures have a significant effect on reducing the risk of potentially risk glacial lakes. At location P2, no floods reached this area after implementing the measures.

4. Discussion

4.1 Uncertainties in GLMS performance

Evaluating the effectiveness of China's GLMS in mitigating the GLOFs impact is subject to several uncertainties due to the data limitations and model constraints. A primary source of uncertainty lies in projecting glacial lake expansion, driven by variability in ice thickness estimates. Sensitivity analysis showed that a ±10% variation in ice thickness altered projected lake area by ±10% but lake volume by ±30%, with extreme deviations (50% increase) yielding a 270% volume rise, while a 50% decrease reduced volume by 89% (Section 3.2, Fig. S9 online). These discrepancies, stemming from subglacial topography and outlet elevation in steep regions (Fig. S15 online), highlight the challenge of accurately modeling lake depth. Validation against remotely sensed glacial lake extents from 2000 to 2020 shows that our thickness-based simulations align well with observations, with errors between 7.5×10^{-4} km^2 (25th percentile) and 1.1×10^{-2} km^2 (75th percentile), and a strong correlation (R^2 = 0.99) (Fig. S16 online). Comparisons with ice thickness estimates from Farinotti et al. [51] and Millan et al. [52] revealed disparities, with predicted lake areas differing by -24% to +9% and volumes by -59% to +102% (Table S5 online). Field observations also confirm our model's projections, showing topographic constraints limit Jiongpu Co and Gangxi Co's expansion, unlike Laigu and Guangxie Co, while inconsistent boundaries in Farinotti et al. [51] and Millan et al. [52] lead to inaccurate predictions (Fig. S17 online). Sediment accumulation, with ~40% of overdeepenings not forming lakes and 45% of new lakes disappearing [53, 54], and GLOF-induced outlet elevation drops by ~20 m (Fig. S18 online) further obscure volume projections, hindering accurate prioritization [49].

Last, the focus on engineering interventions excludes EWS and capacity building, which are hard to quantify, and omits future exposure changes, suggesting the 20% flood intensity reduction is conservative (Section 3.3, Fig. 4). Additional uncertainties stem from the comparative damage analysis (1990–2018 vs. 2019–2023), where the relatively short post-2019 period limits the sample size, potentially reducing the statistical power. However, we validated these findings through multiple approaches, including documented case studies and complementary simulation analyses, which collectively support the robustness of our damage reduction estimates. Simulation assumptions in r.avaflow and HEC-RAS (Section 2.3) oversimplify site-specific dynamics, such as landslide-induced outbursts [55]. These limitations underscore the need for enhanced data collection, longer-term monitoring, and adaptive strategies to optimize GLMS deployment.

4.2 GLMS recommendations for high mountain regions across and beyond the Himalaya

China's GLMS, implemented in 2019, has shown potential to mitigate GLOF impacts through integrated monitoring, engineering, and governance (Fig. S5 online). However, high economic costs and inadequate cross-border information sharing constrain GLMS scalability in the whole Himalaya region. We propose an integrated technical-sociopolitical framework built on the GLMS's strengths while addressing its limitations to provide a scalable solution for GLOF mitigation across the Himalaya (Fig. 5). The key differences include: (1)

emphasis on community-driven early warning systems vs. top-down approaches, (2) transboundary collaboration mechanisms, and (3) distributed rather than centralized decision-making.

Large-scale engineering interventions for all high-risk lakes are neither feasible nor sustainable due to high costs, logistical and technical constraints, and potential environmental consequences (Fig. S19 online). While reinforced dams and spillways can reduce flood intensity, they do not eliminate risk entirely, as even small outburst events can erode sediments and damage infrastructure [56, 57]. In some cases, engineering measures may have minimal or even adverse effects [33, 58]. Given the high costs and site-specific challenges of mitigation projects, a thorough feasibility assessment considering cost performance, the future lake development and intervention effectiveness should be conducted before implementation. In this study, we strongly recommend engineering interventions for lakes that have high development potential and pose significant future GLOF threats (Fig. 4). Implementing these measures early will maximize benefits by proactively reducing flood risks. The required water-level reductions to prevent downstream infrastructure impacts can be estimated accordingly. In contrast, large-volume lakes with limited potential for further expansion are not recommended for engineering interventions. Due to their substantial capacity and minimal expected change, preemptive water release from these lakes would have little effect on overall risk, making engineering the least effective mitigation option. Instead, EWS and other downstream measures should be prioritized to manage potential hazards, such as Cirenma Co [18]. This reflects the experience of "one lake, one strategy" principle in GLMS, where customized management approaches are tailored to each lake's specific risk profile and cost-effectiveness considerations (Figure 1a).

Investments in EWS should prioritize reliability and targeted coverage for high-risk lakes, rather than generalized deployment. Since the establishment of four EWS outside China, 15 GLOFs have occurred since 2019, seven of which caused significant infrastructure damage, and two resulted in fatalities (Table S2 online). Despite the potential of EWS, their implementation still lags behind the number of high-risk glacial lakes [18]. Community-based, informal EWS can serve as an effective complement to formal systems, especially for vulnerable communities. For example, during the Pemdang Pokhari GLOF, upstream warnings of extreme rainfall, flooding, and landslides enabled rapid evacuations, preventing casualties. Similarly, eyewitness alerts allowed for a 30-minute evacuation during the 2020 Jiweng Co outburst in China, averting injuries. Despite $3 billion in Tibetan investments in flood control measures and drills, these efforts may have limited effectiveness without reliable EWS support, as demonstrated by the 2023 South Lhonak Lake disaster in Sikkim [5, 59]. These cases highlight the importance of integrating community-driven EWS with China’s GLMS to enhance reliability, coverage, and resilience, especially in areas where formal systems may fail (Table S2 online).

No single measure can fully mitigate GLOF risks in densely populated high-mountain regions. A comprehensive strategy requires an integrated approach that combines various EWS, engineering interventions, capacity-building initiatives, and active community engagement through awareness programs and emergency drills (Fig. 5). China’s GLMS offers a structured framework for regions that lack effective GLOF mitigation strategies. Building such a comprehensive system is a complex task, involving the integration of social, political, and environmental considerations, alongside strong governmental and societal support. While the centralized governance model in China has been effective, it may not be easily replicable in neighboring countries. Therefore, effective disaster management calls for regional cooperation between China and its neighbors, emphasizing intergovernmental collaboration, joint research efforts, and enhanced data and information sharing [60].

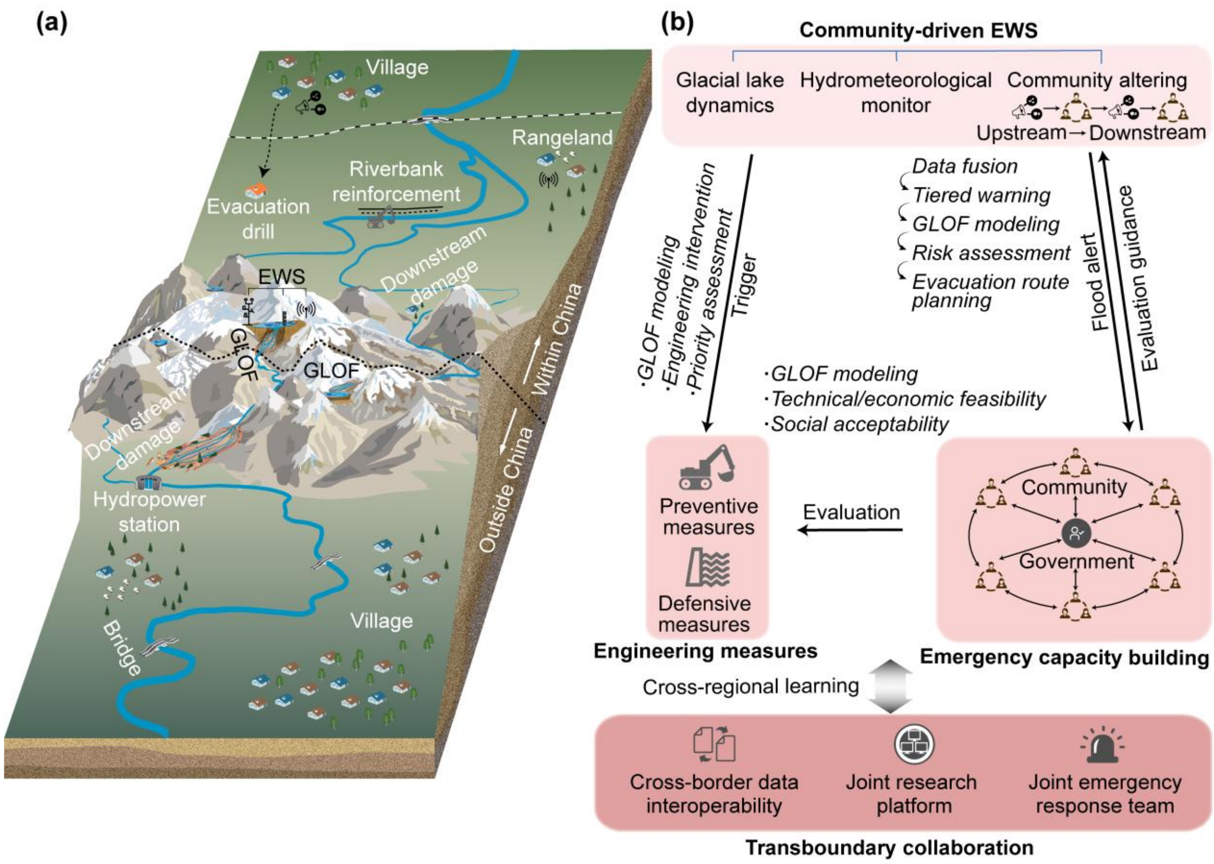

Fig. 5. A new framework for GLOF mitigation across the Himalaya. (a) A schematic diagram of the new framework. (b) A flowchart of the proposed new framework, which integrates community-driven EWS, engineering interventions, emergency capacity building and transboundary collaboration to effectively reduce future GLOF risk across the Himalaya. The framework emphasizes scientific hazard assessment and engineering feasibility evaluation as foundational elements for risk management decisions. Critical upstream-downstream information exchange, particularly across international borders, ensures timely warning dissemination and coordinated response efforts. The system incorporates real-time data fusion for risk assessment, tiered warning systems, and evacuation planning, with enhanced community emergency response capabilities through continuous training and capacity building programs. Key components include multi-level coordination from local community alerting and monitoring to regional cross-border cooperation, integrating both proactive mitigation measures and passive defense strategies through continuous feedback loops between government agencies and communities.

5. Conclusions

This study introduces China's GLMS and demonstrates its effectiveness in mitigating the GLOF damage across the Himalaya. Although the overall frequency of GLOFs has shown a weak decreasing trend over the past three decades, the damage to downstream communities and infrastructure has escalated due to rising exposure and vulnerability. The GLMS exemplifies a proactive, integrated approach to GLOF mitigation. We demonstrate that a combination of EWS, engineering interventions, and community preparedness measures can significantly reduce GLOF risks. In particular, controlled water level drawdown has the potential to reduce flood intensity by up to 24%.

Building on the proven effectiveness of GLMS and considering the transboundary nature of GLOFs, we propose a holistic framework for region-wide risk management that integrates scientific research, engineering solutions, policy frameworks, and community engagement. This framework emphasizes the urgent need for enhanced regional disaster preparedness, improved land-use planning, and strengthened transboundary cooperation.

The China's GLMS offers a valuable model for scaling up mitigation efforts in the Himalaya and beyond. However, continued research and investment are critical to ensure the sustainability and regional applicability of these solutions. By improving EWS, enhancing infrastructure resilience, and promoting international cooperation, we can better protect vulnerable populations from glacier-related geohazards in a changing climate.

Competing interests

The authors declare no competing interests.

Acknowledgements

This study was supported by grants from the National Natural Science Foundation of China (grant no. 42571153; 42301150; 42301140), the China Post-Doctoral Program for Innovative Talents (grant no. BX20230387), the Basic Excellent Research Group for Tibetan Plateau Earth System, National Natural Science Foundation of China (NSFC ERGTPES project No. 42588201), the Department of Science and Technology of the Tibet Autonomous Region (XZ202403ZY0028), and the Second Tibetan Plateau Scientific Expedition and Research Program (2019QZKK0201). AE acknowledges the support from the HINTERLANDS project (High mountains in the Anthropocene: from landscape dynamics to hazards and risks; PRIMUS/25/SCI/005) realized at the Charles University, Faculty of Science; and Johannes Amos Comenius Programme (P JAC), project No. CZ.02.01.01/00/22_008/0004605, Natural and anthropogenic georisks.

Author contributions

Wenfeng Chen and Guoqing Zhang designed the study, and Xue Wang and Wenfeng Chen drafted the manuscript. All authors contributed to the final form of the study.

Data availability

Landsat imagery can be downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). Sentinel imagery can be downloaded from https://dataspace.copernicus.eu. NASADEM data can be downloaded from https://search.earthdata.nasa.gov. Glacial lake inventory in 2020 can be downloaded from https://doi.org/10.6084/m9.figshare.21708590. The bathymetric measurements for Jialong Co are available at https://doi.org/10.6084/m9.figshare.21569175. All process documents including future glacial lake extent, bathymetry, ice thickness and GLOF inventory and simulation outputs are available at https://zenodo.org/records/16410526.

Code availability

Scripts for the ice thickness inversion model and r.avaflow simulations are available at https://github.com/cnugis/icethicknessmodel-lake_terminating_galcier.

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