Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 02, February-2025

Glacier Flood Detection using Deep Learning Through Satellite Images

Ms. Nishigandha Shirsath
Pillai College of Engineering,
New Panvel, Mumbai

Prof. Varunakshi Bhojane
Pillai College of Engineering,
New Panvel, Mumbai

***Abstract*— For outburst susceptibility assessment of glacial lakes, the accurate extraction of glacial lakes region from satellite image is essential. Several techniques are introduced to extract glacial lakes over the years, such as based on image pixel or different thresholds and object-based statistics. These methods require manual optimization parameters for accurate extraction of the glacial lake's region. DL techniques are successful in many research areas for classification problems, but these techniques are relatively new for the extraction of glacial lakes. This project addresses the critical issue of glacier flood detection by harnessing the capabilities of deep learning applied to satellite imagery. Glacier floods, or glacial outburst floods (GLOFs), present a significant threat to both human settlements and ecosystems due to their sudden and devastating nature. Traditional methods of monitoring and predicting these events are often hindered by manual analysis and resource-intensive processes. The primary objective of this research is to develop a robust deep learning model capable of early detection of glacier floods through the analysis of satellite imagery. Leveraging state-of-the-art deep learning techniques, our model aims to provide timely and accurate alerts, enhancing the efficiency of early warning systems. The methodology involves the collection and preprocessing of satellite imagery data, followed by the implementation of a deep learning model trained to recognize patterns indicative of potential glacier flood events. Evaluation metrics, including precision, recall, and F1 score, will be employed to assess the model's performance.**

***Keywords*— CNN, Deep Learning, GLOF's.**

I. INTRODUCTION

Floods are one of the most harmful natural disasters, causing major damage to buildings, farms, and homes. Whether brought on by glacial outbursts, river floods, storm surges, or heavy rain, these events can have major social and financial repercussions. Effective disaster response, mitigating, and long-term planning depend on early, accurate flood detection given their destructive power. With artificial intelligence (AI) and deep learning providing interesting solutions, the integration of cutting-edge technological approaches in flood detection has grown ever more crucial. Particularly for image analysis and pattern recognition, convolutional neural networks (CNNs) have become an increasingly effective tool offering fresh chances for real-time flood detection and monitoring.

Recent developments in remote sensing technologies have improved the accuracy with which one may monitor and forecast flood events. High-resolution images produced by satellites and unmanned aerial vehicles (UAVs) can be examined to identify flood-prone regions and spot actual flood events. Nonetheless, conventional flood detection techniques—which frequently rely on hydrological models and hand interpretation of satellite images—can be time-consuming and prone to mistakes. CNNs in particular have shown amazing ability to automate the analysis of satellite and aerial images, so enabling faster and more exact flood detection. CNNs can be trained to identify flood patterns, separate water from land, and highly accurately classify impacted areas by using big datasets.

Aiming to solve current constraints and improve detection accuracy and speed, this research article suggests an approach for flood detection using CNNs. CNNs are applied in flood detection to classify flood-affected areas, extract pertinent features from vast amounts of satellite images, and process CNNs' ability to learn hierarchical features via convolutional layers—which helps them to capture spatial patterns and textures inside images—helps to explain their general effectiveness in this field. CNNs are quite efficient for image classification tasks since they automatically learn and optimize features unlike conventional machine learning techniques, which frequently depend on hand feature extraction.

The variability in flood properties over various geographical areas presents one of the main difficulties in flood detection. The occurrence and degree of floods are influenced by topography, climate, land use, and hydrological conditions. Consequently, building a strong CNN-based flood detection model calls for a varied and extensive dataset covering many flood situations. Training and validation of deep learning models depend on the availability of excellent labelled datasets. Many times, CNN models benefit much from publicly available satellite imagery datasets including those from NASA and the European Space Agency (ESA). Furthermore, improving model performance is the inclusion of auxiliary data including hydrological criteria and meteorological information.

Furthermore, important for CNN-based flood detection is the network architecture choice. Image classification and segmentation challenges have investigated many CNN architectures, including VGGNet, ResNet, and U-Net. U-Net and Fully Convolutional Networks (FCNs) have shown especially great promise in the context of flood detection because of their ability to perform pixel-wise segmentation, so allowing exact delineation of flooded areas. These systems use an encoder-decoder design whereby the decoder reconstructs the segmentation map from an encoder extracting features from input images. Skip connections in U-Net help to preserve spatial information, so enhancing segmentation accuracy.

There are still several difficulties even with CNN-based flood detection's benefits. Commonly used in CNNs to lower dimensionality, the max-pooling process causes a loss of spatial information, hence one of the main restrictions is Max-pooling can cause the loss of fine-grained details vital for accurate flood boundary detection even while it helps capture high-level features. Alternative pooling techniques including atrous convolution and attention mechanisms have been investigated to improve spatial resolution while preserving computational efficiency in order to help to solve this problem.

The generalizing of CNN models across several flood scenarios presents still another difficulty. Location, topography, and climate all affect the unique qualities of floods. Applied to a different area with unique flood patterns, a model trained on a particular dataset may not perform well. A possible answer to this issue is transfer learning methods, whereby a pre-trained CNN model is refined on a target dataset. Leveraging knowledge from pre-trained models, transfer learning helps CNNs to adapt to new datasets with few labeled samples, so enhancing model generalization and lowering training time.

Further improving flood detection performance is the inclusion of other data sources including remote sensing and meteorological information. For flood analysis, remote sensing technologies—including optical imagery and synthetic aperture radar (SAR—have complimentary information. Particularly SAR is quite good for flood detection since it can pass clouds and function in all kinds of weather. By capturing both structural and spectral aspects of flood-affected areas, combining SAR and optical imagery in a CNN framework can enhance detection accuracy. Furthermore adding real-time weather data—such as river discharge rates and precipitation levels—can provide early warning systems and flood prediction useful contextual information.

Particularly in high mountain areas where glacier-fed lakes are expanding as a result of climate change, glacial outburst floods—also known as glacial lake outburst floods (GLOFs—represent a major environmental concern. Rapid meltwater release from glaciers can cause disastrous flooding that threatens ecosystems and downstream towns. Detecting GLOFs calls for specific methods that consider the dynamic character of glacial lakes and surrounding landscape. Often labor-intensive and costly, traditional field-based studies for long-term monitoring of glacial lakes are Conversely, combined with deep learning approaches, remote sensing-based solutions provide a scalable and reasonably priced way to monitor glacial lakes and project possible outburst events.

Although deep learning methods have shown great success in many fields of research, their use to glacial lake extraction and GLOF detection is rather new. CNN-based segmentation models are ideally suited for the segmentation of water bodies from surrounding land and ice involved in the extraction of glacial lakes from satellite imagery. Still, in this context the availability of labeled datasets for training deep learning models presents a difficulty. Glacial lake boundary manual annotation takes time; variations in image quality and lighting conditions make the work more difficult. To overcome the lack of labeled data and enhance model robustness, semi-supervised and unsupervised learning methods including generative adversarial networks (GANs) and self-supervised learning have been investigated.

Urban planning, early warning systems, and disaster management systems are just a few of the several possible uses for the proposed CNN-based flood detecting method. CNN-based real-time flood monitoring can support emergency responders in quickly evaluating impacted areas and distributing resources. By combining CNN-based flood detection with meteorological data, early warning systems can give at-risk populations timely warnings so lessening the impact of flood events. Urban designers can also evaluate flood-prone areas using flood detection models and create strong infrastructure to reduce present risks.

Future directions in CNN-based flood detection consist in developing multimodal fusion techniques, improving model interpretability, and raising computational efficiency. By means of explainable artificial intelligence (XAI) techniques such Grad-CAM and SHAP, CNN decision-making processes can be revealed, so fostering trust and dependability in flood detection systems. Real-time flood detection in resource-limited settings can be enabled by optimizing CNN architectures for edge computing and implementing models on low-power devices. Moreover, including multimodal data sources— LiDAR, thermal images, social media reports—helps to improve situational awareness and flood prediction capacity.

To sum up, CNN application in flood detection marks a major progress in disaster response and monitoring. Flood detection systems can reach better accuracy, faster processing times, and increased scalability by using deep learning methods. Even if problems including data availability, model generalization, and spatial resolution still exist, constant research and technological developments help to solve these problems. Flood detection and early warning systems could be much improved by combining remote sensing, meteorological data, and multimodal techniques. Innovative and efficient flood detection techniques become ever more important as climate change increases the frequency and intensity of floods. CNN-based flood detection can significantly help to reduce the effects of floods and safeguard sensitive areas by means of ongoing research and development.

II. LITERATURE SURVEY

High Mountain Asia (HMA) holds the largest concentration of glacier ice outside the polar regions, with approximately 95,000 glaciers (Guillet et al., 2022). The region also contains around 30,000 glacial lakes, spanning an area of nearly 2000 km² (Wang et al., 2020). Since the 1960s, glaciers in HMA have been retreating and experiencing mass loss at rates ranging from 0.06 to 0.4 meters water equivalent per year (Bhattacharya et al., 2021). This retreat has led to the formation and expansion of glacial lakes (Nie et al., 2017; Shugar et al., 2020; M. Zhang et al., 2021), some of which have triggered glacial lake outburst floods (GLOFs) (Carrivick and Tweed, 2013; Nie et al., 2018; Song et al., 2016; Veh et al., 2019b). GLOFs have been documented globally, including in the European Alps (Huss et al., 2007), the Andes (Iribarren Anacona et al., 2014), North America (Wilcox et al., 2014), and the Hindu Kush Himalaya (Ives et al., 2010; Mool et al., 2001; Rounce et al., 2017).

Published by :
http://www.ijert.org
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 02, February-2025

Studies indicate that glacial lakes in HMA have expanded in both number and total area since the 1990s (Chen et al., 2021; Shugar et al., 2020; Wang et al., 2020; Zhang et al., 2015; Zheng et al., 2021a). Between 1990 and 2015, lake numbers increased by 5.9%, while their total area expanded by 6.8% ± 0.1% (Zheng et al., 2021a). Other studies have reported increases of 2916 lakes and 273.65 km² from 1990 to 2018 (Wang et al., 2020) and 3342 lakes and 220.64 km² between 2009 and 2017 (Chen et al., 2020). The expansion has primarily been attributed to the growth of proglacial moraine-dammed lakes (Zheng et al., 2021a; Nie et al., 2013; Gardelle et al., 2011), with the number of glacier-contact proglacial lakes increasing by 31.3% ± 0.3% between 1990 and 2015 (Zheng et al., 2021a) and by 96.27 km² (57%) from 1990 to 2018 (Wang et al., 2020).

Regional studies suggest that the ongoing expansion of glacial lakes (Gardelle et al., 2011; Shugar et al., 2020) could create new hotspots of hazardous lakes (Furian et al., 2022; Linsbauer et al., 2015; Zhang et al., 2022a; Zheng et al., 2021a), posing increased risks of GLOFs (Haeberli et al., 2016). Several processes have been identified as GLOF triggers, including dynamic slope movements (avalanches, rockfalls, and landslides) that displace lake water (Awal et al., 2010; Jiang et al., 2004), glacier calving (Emmer and Cochachin, 2013; Westoby et al., 2014; Worni et al., 2014), and extreme precipitation or ice melt causing water levels to rise suddenly (Allen et al., 2016; Cook et al., 2018; Worni et al., 2012). Seismic activity has also been identified as a destabilizing factor for moraine dams, increasing the likelihood of failure (Osti et al., 2011; Somos-Valenzuela et al., 2014; Westoby et al., 2014). Additionally, seepage, piping, and the degradation of ice-cored moraines contribute to dam failures over time (Mool et al., 2001; Yamada and Sharma, 1993).

Historical assessments indicate that GLOFs have resulted in over 12,000 fatalities and caused extensive damage to infrastructure and farmland over the past century (Carrivick and Tweed, 2016). With increasing population density and infrastructure development in downstream areas, the exposure of communities to GLOF risks is rising (Li et al., 2022). Implementing timely risk reduction strategies is therefore essential but remains challenging, particularly in politically sensitive regions (Allen et al., 2019; Khanal et al., 2015).

Numerous studies have examined the causes, mechanisms, and trends of GLOFs over the past few decades (Allen et al., 2016; Dwiwedi et al., 2000; Ives, 1986; Mool et al., 2001; Nie et al., 2020; Zheng et al., 2021c). Research on GLOFs in HMA has expanded significantly in recent years (Emmer et al., 2022), with many studies focusing on individual events. While some studies have attempted to consolidate data on GLOFs in HMA, they often have geographical limitations (Nie et al., 2018; T. Zhang et al., 2021; Zheng et al., 2021b) or focus only on specific types of GLOFs (Veh et al., 2019a). A recent global study has attempted to bridge these gaps (Veh et al., 2022), though it does not address GLOF impacts in detail. Many past events have been omitted from previous records due to a lack of reporting in scientific literature, with some only documented in local media sources (Veh et al., 2022; Zheng et al., 2021b).

More comprehensive datasets are needed to address these gaps (Emmer et al., 2022), especially as research shifts from hazard assessments to risk evaluations that include transboundary dimensions (Zheng et al., 2021a). Future studies could benefit from a dynamic database that tracks changes over time and allows for continuous updates (Blischak et al., 2016). Such a database has already proven useful in cryospheric research (Welty et al., 2020) and could establish standards to improve data accessibility (Mankoff et al., 2021; Welty et al., 2020). Importantly, this database should be designed for accessibility not only by scientists but also by policymakers and other stakeholders unfamiliar with machine-readable data.

In this study, we aim to (a) compile a comprehensive dataset of GLOFs in HMA, including their locations, timing, associated processes, and downstream impacts; (b) integrate records from scientific literature with local sources to identify previously undocumented events; and (c) demonstrate the potential of making such a dataset fully accessible and interoperable with other geospatial datasets.

III. METHODOLOGY

A. Compilation of GLOF data

To compile historical data on glacial lake outburst floods (GLOFs), we conducted a comprehensive review of peer-reviewed articles, book chapters, technical reports, news sources, and social media posts, with a final cut-off date of June 30, 2022. The resulting database includes 115 publications, consisting of 83 peer-reviewed journal articles, 16 book chapters, and 16 technical reports, along with nine online news articles and three social media posts. Additionally, anecdotal accounts from local sources, collected during fieldwork in affected areas, were incorporated to enhance data coverage.

Identifying historical GLOFs presents challenges due to limited accessibility of reports and the likelihood of unrecorded events, particularly in remote regions with minimal impact on human settlements and infrastructure. To address this, we included events documented in scientific literature, regional media, local civil society organizations, and firsthand accounts. While peer-reviewed studies often focus on well-researched catchments, news reports highlight events with significant socio-economic impacts. Satellite imagery provides an independent verification tool but is limited for pre-20th-century events. Local knowledge contributes valuable insights but may be subject to memory degradation and misidentification.

Misidentification remains a concern, as non-GLOF events, such as debris flows or pluvial floods, are sometimes erroneously classified as GLOFs. To ensure accuracy, we verified sources using satellite imagery, assessing key indicators such as moraine breaches, rapid lake area changes, and exposed lake beds. High-resolution Maxar satellite images were consulted for validation, and cases lacking sufficient verification were excluded from the final dataset.

We also documented GLOFs without clear glacial associations, either due to uncertain upstream connections or the absence of adjacent glaciers in available inventories. To facilitate regional comparisons, GLOF locations were georeferenced and categorized based on multiple regional

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 02, February-2025

delineations, including the Randolph Glacier Inventory and HiMAP framework, ensuring compatibility for policy and research applications.

B. Data structure and recorded variables

To ensure transparency and usability, the database provides full access to data files and processing code. The database stores doubtful or non-GLOF events in HMAGLOFDB_removed.csv, while all GLOF events are in HMAGLOFDB.csv. HMAGLOFDB_Metadata.yml describes data files and variables in YAML format for machine- and human-readable access.

All events have a unique number. The event date is recorded where available; if the flood lasted multiple days, only the peak flood day or last drainage day is recorded. If the year is uncertain, original sources or satellite imagery provide a range or latest possible occurrence date (Year_approx). Satellite IDs (Sat_evidence) link new events without years. Lakes and glaciers have local names, but use them cautiously due to inconsistencies.

The database aids hazard mapping and impact analysis by recording source and downstream impact locations. Source coordinates are usually within a lake outline, while impact locations are the furthest flood effects or sediment deposits visible in Maxar imagery. Original reports or Shuttle Radar Topography Mission (SRTM) digital elevation models provide elevation data.

Lakes can be moraine-dammed, ice-dammed, bedrock-dammed, supraglacial, or subsurface. The 2022 national borders suggest transboundary effects, but they do not confirm cross-border flood movement. Country, province, river basin, and mountain region details help stakeholders unfamiliar with GIS data.

Lake formation drivers (Driver_lake), GLOF triggers (Driver_GLOF), and drainage mechanisms (Mechanism) improve numerical modeling and climate risk assessment. Lake area, drained volume, and water and solid discharge data from reports are essential for infrastructure planning and disaster mitigation. Data estimates vary, with some using rough calculations.

To comply with the Sendai Framework's call for inclusive disaster data, impact data include fatalities by gender and disability. Insufficient fatality data shows disaster reporting gaps. The number of affected houses, hydropower facilities, agricultural land, and livestock losses are other impact indicators. Estimates of economic damages (Econ_damage) are incomplete.

Each event has full citations (Ref_scientific_full) or newspaper links (Ref_other) for scientific, media, and oral sources. Events in HMAGLOFDB_removed are non-GLOF.Exclusion reason (Removal_reason) and certainty indicator (Certainty) distinguish confirmed non-GLOFs from uncertain cases in csv.

This database is compatible with cryospheric datasets like glacier outlines, elevation changes, glacial lakes, and permafrost extents. For seamless data fusion, it integrates spatial identifiers like GLIMS glacier IDs (G_ID) and glacial lake IDs (GL_ID).

Future updates will be in GitHub development, ensuring continuous improvement. Annual quality checks will verify new events with fieldwork and depth. Researchers and policymakers will have access to a revised database under the same DOI.

IV. RESULTS

We have 697 GLOF events from 1833 to 2022, with four predating this period that are nearly impossible to validate. These include 46 events (7%) that have not been previously studied, and 101 previously reported GLOFs were removed due to contradictory evidence (17) or insufficient data (84) supporting their classification.

China had 28.4% of recorded events, Kyrgyzstan 24.7%, Pakistan 21%, India 8.5%, Nepal 7.6%, Kazakhstan 4.9%, Bhutan 2.9%, Tajikistan 1.6%, and Afghanistan 0.6%. According to the RGI, 30% were in the Karakoram, 18% in the Eastern Himalaya, and 29% in the Western Tien Shan. Different delineation methods affect HiMAP outlines, which place 28% in the Karakoram, 17% in the Northern/Western Tien Shan, 14% in the Central Himalaya, and 10% in the Eastern Himalaya.

A month is known for 47% of events, with 74% occurring between June and August. Only 3% occurred in November–March. The exact day of the event is known for 275 cases (39%), allowing weather pattern analyses before the GLOF.

GLOF lakes average 4598 m a.s.l., ranging from 2562 to 5982 m. The mean elevation difference between the source lake and the lowest recorded impact point was 1161 m a.s.l. in 66% of events.

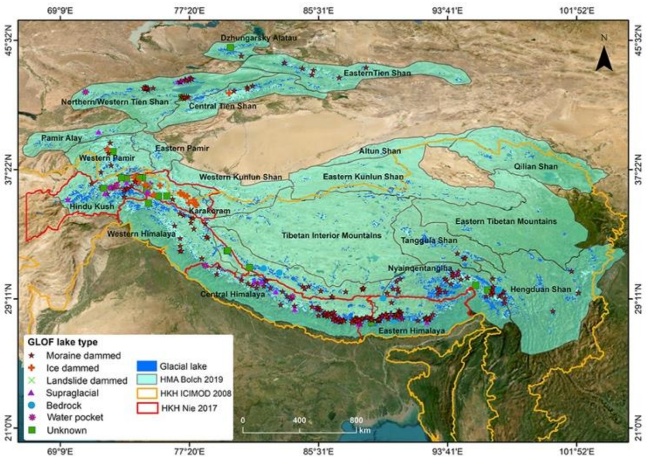

Image 1: A map showing all recorded GLOFs in the HMA by lake type, based on the 2018 lake inventory from Wang et al. (2020). The HMA outline follows Bolch et al. (2019), with external lake databases (WangDB, ChenDB) within this boundary. The HKH outline is based on ICIMOD (https://rds.icimod.org/Home/DataDetail?metadataId=_3924 , accessed 17 July 2023) and Nie et al. (2017).

Moraine-dammed lakes had 47% of events, ice-dammed 34%, and supraglacial 10%. Water pockets, bedrock lakes, and landslide-dammed lakes rarely produced englacial outbursts. Certain events in the Upper Indus and Ala Archa basin suggest water pocket drainage rather than surface lake drainage. The evidence is inconclusive. Lake type is

Published by :
http://www.ijert.org
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 02, February-2025

unknown in 4% of cases due to a lack of satellite imagery validation.

Only 20% of lake formation mechanisms, 12% of triggers, and 26% of failure mechanisms are known. Total drained volume (15%), water discharge (10%), and sediment discharge (3%), all important for modeling, are even less known. Reports often have large uncertainties.

There were two GLOFs in areas without an upstream glacier, suggesting they existed. 22 GLOFs occurred below glaciers absent in RGI 6.0, and 10 moraine-dammed GLOFs had no satellite-visible lakes, possibly due to pre-satellite events. 97 events involved unmapped lakes or depressions, and 28% involved ephemeral lakes not inventoried.

25 GLOFs killed 6906 people, including 6000 in India in 2013. Most deaths occurred in moraine-dammed or supraglacial lakes. Infrastructure damage included 2200+ buildings, bridges, and 71 km² of farmland. Damaged were 164 MW hydropower plants. Economic losses, excluding long-term effects, were $5.3 billion in 13 cases.

Of 338 lakes linked to GLOFs, 61 (18%) caused multiple events. At least five GLOFs occurred in 17 lakes, 43% of all events. Ice-dammed lakes often drain again, but the Himalaya and Tibetan Plateau rarely do.

Image 2: (a) The 1985 Dig Tsho GLOF in Nepal's Central Himalaya (GF_ID 322) from a moraine-dammed lake, impacting settlements and agricultural land in the lower reach. Photo taken in 2009 (credit: Sharad Joshi). (b) The 2021 Bam Tanab GLOF in Afghanistan's Hindu Kush (GF_ID 510) from a supraglacial lake, with the visible ice tunnel through which the lake drained. Photo taken several days after the event (credit: Milad Dildar). (c) Ice tunnel exit at Badswat Glacier in Pakistan, causing a 2018 GLOF that eroded the moraine downstream (GF_ID 493; photo credit: Sher Wali). (d) Ice dam at Khurdopin Glacier, where the lake refills after a surge, with visible water lines indicating multiple refills (GF_ID 26; photo credit: Sher Wali).

Of all events, 190 (27%) were potentially transboundary, with 55 from China. Fewer than 10 cases had cross-border impacts, mostly from China to Nepal and Uzbekistan to Kyrgyzstan.

V. GLOF PATHS

Records of 459 GLOF events allow evaluation of GLOF paths and drivers and impacts (Fig. 6). We can identify triggers by comparing GLOF occurrences with lakes that have not outburst using spatial datasets like decadal glacier outlines (He and Zhou, 2022; Lee et al., 2021; Xie, 2023), ice mass loss (Brun et al., 2017; Hugonnet, 2021), permafrost probability (Obu, 2021), and snow cover (Muhammad and Thapa, 2021). Recent glacier retreat and moraine stability make areas with recent permafrost change more susceptible to mass movements, which cause GLOFs (Fig. 4). Rapid temperature increases are often blamed for GLOFs, but no studies have linked ice or snow melt to lake drainage or dam failure.

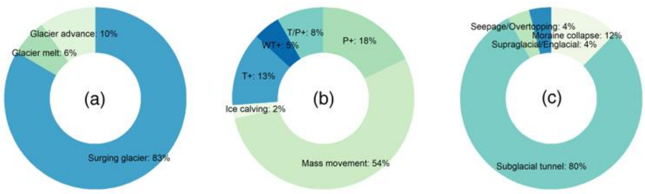

Fig: 4 : Drivers of lake formation (139) and GLOF occurrence (84) include various factors: (a) lake formation is influenced by glacier melt, temperature, precipitation, and water table increases, (b) GLOFs are caused by these factors as well as mass movements (ice and rock avalanches, landslides, debris flows), and (c) mechanisms of lake drainage include moraine collapse (often due to ice core thawing) and seepage/overtopping, which also involves piping through the dam.

Downstream, infrastructure, population, and ecosystem datasets reveal impacts and vulnerabilities (Fig. 6). By coupling GLOF paths with population data (Thornton et al., 2022), remotely sensed vegetation and agricultural data can estimate the number of people affected and assess local economic and ecological impacts. Like avalanche-prone area zonation maps, these paths can inform hazard zonation maps.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 02, February-2025

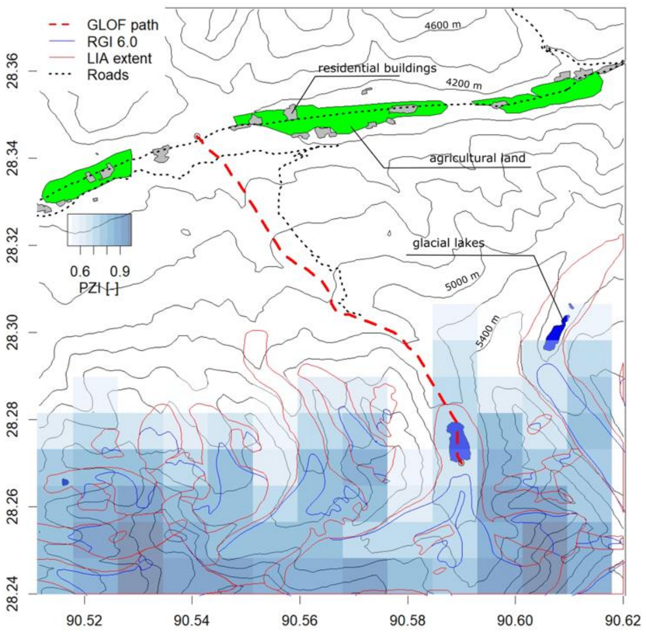

Fig: GLOF path for event GF_ID 651, showing the RGI 6.0 outline, possible glacier extent during the Little Ice Age (Lee et al., 2021), and permafrost probability (PZI, Obu, 2021). Roads are from OpenStreetMap, and residential/agricultural areas from Maxar imagery. The figure can be generated using R code from the database for any event.

We can calculate reach angles to estimate flood path distances using the lake's location and the lowest GLOF evidence (flood or debris deposits) (Fig. 7). Current studies use estimated runouts (Schwanghart et al., 2016; Taylor, 2023) instead of reach predictions, which are less accurate. GLOF reach predictions are uncertain, but this study provides glacier size and path topography-based ranges. A median reach angle of 0.14 (8°) suggests that GLOFs travel further than glacier detachments and set an upper bound for future events.

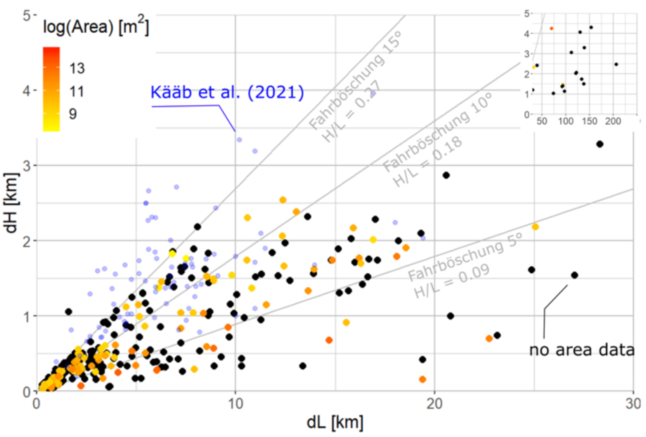

Fig: Reach angles for 459 GLOF events with recorded downstream impacts are shown. Black dots represent events with no lake area records, while shaded yellow to red indicates events with available lake area data, which may not reflect pre-event sizes. Light blue indicates records from Kääb et al. (2021), mostly related to glacier detachments or large-scale debris flows and GLOFs.

VI. CONCLUSION

In this study, we present a comprehensive compilation of GLOF events in High Mountain Asia from the mid-19th century to 2022. The inventory is machine-readable, version-controlled, and will be regularly updated with new events. It includes key details on time, location, processes, and impacts, and is linked to glacial lake and glacier inventories, facilitating future studies on GLOF drivers. Of the 697 recorded events, 47% have a known month of occurrence, enabling seasonal analysis, and 39% have a recorded day of drainage, allowing for studies on weather patterns prior to events. Additionally, 52% of GLOFs are associated with a lake from at least one inventory, and 95% with a mapped glacier, providing insight into how glacier mass loss and lake area changes influence GLOF occurrences.

We observe significant regional differences in the types of lakes associated with GLOFs, with few ice-dammed lakes in the Himalaya and even fewer moraine-dammed lakes in the Karakoram. While mechanisms of lake formation and drainage are documented for only a few events, the dataset provides a useful proxy for flood volumes and potential reach using lake area changes. Notably, GLOFs generally do not exceed reach angles of 15° (with larger events traveling even less), which can aid future hazard mapping.

The dataset also reveals that 906 deaths were directly linked to GLOFs—three times higher than previously reported. Despite this, GLOFs have caused relatively fewer human fatalities compared to other regional mountain hazards. Impacts, however, are often poorly documented, especially injuries, property damage, and long-term economic effects. Seven percent of the recorded events were previously unreported, highlighting the importance of including diverse sources, including local and oral accounts. Future research should focus on improving damage assessment methods and documenting indigenous knowledge on GLOF hazards.

As understanding of the cryosphere in HMA continues to grow, future studies should integrate GLOF and lake inventories with upstream processes that could lead to cascading hazards. Expanding documentation of other mountain hazards in compatible formats will support regional studies and hazard modeling.

REFERENCES

[1] Acharya, A., Steiner, J. F., Walizada, K. M., Ali, S., Zakir, Z. H., Caiserman, A., & Watanabe, T. (2023). Snow and ice avalanches in high mountain Asia – scientific, local, and indigenous knowledge. Natural Hazards and Earth System Sciences, 23, 2569–2592. https://doi.org/10.5194/nhess-23-2569-2023

[2] Ahmed, R., Ahmad, S. T., Wani, G. F., Mir, R. A., Almazroui, M., Bansal, J. K., & Ahmed, P. (2022). Glacial lake changes and the identification of potentially dangerous glacial lakes (PDGLs) under warming climate in the Dibang River Basin, Eastern Himalaya, India. Geocarto International, 1–27. https://doi.org/10.1080/10106049.2022.2134461

[3] Allen, S. K., Rastner, P., Arora, M., Huggel, C., & Stoffel, M. (2016). Lake outburst and debris flow disaster at Kedarnath, June 2013: Hydrometeorological triggering and topographic predisposition. Landslides, 13, 1479–1491. https://doi.org/10.1007/s10346-015-0584-3

[4] Allen, S. K., Zhang, G., Wang, W., Yao, T., & Bolch, T. (2019). Potentially dangerous glacial lakes across the Tibetan Plateau revealed using a large-scale automated assessment approach. Science Bulletin, 64, 435–445. https://doi.org/10.1016/j.scib.2019.03.011

[5] Ashraf, A., Naz, R., & Roohi, R. (2012). Glacial lake outburst flood hazards in Hindukush, Karakoram, and Himalayan Ranges of Pakistan: Implications and risk analysis. Geomatica, Natural Hazards, and Risk, 3, 113–132. https://doi.org/10.1080/19475705.2011.615344

[6] Ashraf, A., Naz, R., Mustafa, N., Iqbal, M. B., Ahmad, B., Jawad, A., & Ahmad, I. (2015). Updating GLOF lake inventory of Northern Pakistan and establishment of community-based early warning system in Bagrot and Bondo Gol valleys (Technical Report). Pakistan Agricultural Research Council (PARC), Islamabad, Pakistan.

[7] Ashraf, A., Iqbal, M. B., Mustafa, N., Naz, R., & Ahmad, B. (2021). Prevalent risk of glacial lake outburst flood hazard in the Hindu Kush–Karakoram–Himalaya region of Pakistan. Environmental Earth Sciences, 80, 451. https://doi.org/10.1007/s12665-021-09740-1

[8] Awal, R., Nakagawa, H., Fujita, M., Kawaike, K., Baba, Y., & Zhang, H. (2010). Experimental study on glacial lake outburst floods due to waves overtopping and erosion of moraine dam. Annals of Disaster Prevention Research Institute, 53, 583–594.

[9] Bajracharya, S. R., Maharjan, S. B., Shrestha, F., Sherpa, T. C., Wagle, N., & Shrestha, A. B. (2020). Inventory of glacial lakes and identification of potentially dangerous glacial lakes in the Koshi, Gandaki, and Karnali river basins of Nepal, the Tibet Autonomous Region of China, and India. International Centre for Integrated Mountain Development (ICIMOD), United Nations Development Programme (UNDP). https://doi.org/10.53055/ICIMOD.773

[10] Bhattacharya, A., Bolch, T., Mukherjee, K., King, O., Menounos, B., Kapitsa, V., Neckel, N., Yang, W., & Yao, T. (2021). High Mountain Asian glacier response to climate revealed by multi-temporal satellite observations since the 1960s. Nature Communications, 12, 4133. https://doi.org/10.1038/s41467-021-24180-y

[11] Blischak, J. D., Davenport, E. R., & Wilson, G. (2016). A quick introduction to version control with Git and GitHub. PLOS Computational Biology, 12, e1004668. https://doi.org/10.1371/journal.pcbi.1004668

[12] Bolch, T., Buchroithner, M. F., Peters, J., Baessler, M., & Bajracharya, S. (2008). Identification of glacier motion and potentially dangerous glacial lakes in the Mt. Everest region/Nepal using spaceborne imagery. Natural Hazards and Earth System Sciences, 8, 1329–1340. https://doi.org/10.5194/nhess-8-1329-2008

[13] Bolch, T., Shea, J. M., Liu, S., Azam, F. M., Gao, Y., Gruber, S., Immerzeel, W. W., Kulkarni, A., Li, H., Tahir, A. A., Zhang, G., & Zhang, Y. (2019). Status and change of the cryosphere in the extended Hindu Kush Himalaya region. In P. Wester, A. Mishra, A. Mukherji, & A. B. Shrestha (Eds.), The Hindu Kush Himalaya Assessment: Mountains, climate change, sustainability and people (pp. 209–255). Springer. https://doi.org/10.1007/978-3-319-92288-1_7

[14] Brun, F., Berthier, E., Wagnon, P., Kääb, A., & Treichler, D. (2017). A spatially resolved estimate of High Mountain Asia glacier mass balances from 2000 to 2016. Nature Geoscience, 10, 668–673. https://doi.org/10.1038/ngeo2999

[15] Carrivick, J. L., & Tweed, F. S. (2013). Proglacial lakes: Character, behavior and geological importance. Quaternary Science Reviews, 78, 34–52. https://doi.org/10.1016/j.quascirev.2013.07.028

[16] Carrivick, J. L., & Tweed, F. S. (2016). A global assessment of the societal impacts of glacier outburst floods. Global and Planetary Change, 144, 1–16. https://doi.org/10.1016/j.gloplacha.2016.07.001

[17] Chen, F., Zhang, M., Guo, H., Allen, S., Kargel, J. S., Haritashya, U. K., & Watson, C. S. (2021). Annual 30 m dataset for glacial lakes in High Mountain Asia from 2008 to 2017. Earth System Science Data, 13, 741–766. https://doi.org/10.5194/essd-13-741-2021

[18] Cook, K. L., Andermann, C., Gimbert, F., Adhikari, B. R., & Hovius, N. (2018). Glacial lake outburst floods as drivers of fluvial erosion in the Himalaya. Science, 362, 53–57. https://doi.org/10.1126/science.aat4981

[19] Cook, S. J., & Quincey, D. J. (2015). Estimating the volume of Alpine glacial lakes. Earth Surface Dynamics, 3, 559–575. https://doi.org/10.5194/esurf-3-559-2015

[20] Duan, H., Yao, X., Zhang, D., Qi, M., & Liu, J. (2020). Glacial lake changes and identification of potentially dangerous glacial lakes in the Yi'ong Zangbo River Basin. Water, 12, 538. https://doi.org/10.3390/w12020538

[21] Dwiwedi, S. K., Acharya, M. D., & Simard, R. (2000). The Tam Pokhari Glacier Lake outburst flood of 3 September 1998. Journal of Nepal Geological Society, 22, 539–546.

[22] Ebrahim, Z. (2022). Climate disasters trigger mental health crisis in Pakistan's mountains. The Third Pole. http://globeistan.com/?p=101216 (last accessed: 10 January 2022)

[23] Emmer, A., & Cochachin, A. (2013). The causes and mechanisms of moraine-dammed lake failures in the Cordillera Blanca, North American Cordillera, and Himalayas. AUC Geographica, 48, 5–15. https://doi.org/10.14712/23361980.2014.23

[24] Emmer, A., Allen, S. K., Carey, M., Frey, H., Huggel, C., Korup, O., Mergili, M., Sattar, A., Veh, G., Chen, T. Y., Cook, S. J., Correas-Gonzalez, M., Das, S., Diaz Moreno, A., Drenkhan, F.,

[25] Steiner, J. F., Kraaijenbrink, P. D. A., Jiduc, S. G., & Immerzeel, W. W. (2018). Brief communication: The Khurdopin glacier surge revisited – extreme flow velocities and formation of a dammed lake in 2017. The Cryosphere, 12, 95–101. https://doi.org/10.5194/tc-12-95-2018

[26] Taylor, C., Robinson, T. R., Dunning, S. A., Carr, J. R., & Westoby, M. J. (2023). Glacial lake outburst floods threaten millions globally. Nature Communications, 14, 487. https://doi.org/10.1038/s41467-023-36033-x

[27] Thapa, V., & Pathranarakul, P. (2019). Gender inclusiveness in disaster risk governance for sustainable recovery of the 2015 Gorkha Earthquake, Nepal. International Journal of Disaster Risk Reduction, 34, 209–219. https://doi.org/10.1016/j.ijdrr.2018.11.019

[28] Thornton, J. M., Snethlage, M. A., Sayre, R., Urbach, D. R., Viviroli, D., Ehrlich, D., Muccione, V., Wester, P., Insarov, G., & Adler, C. (2022). Human populations in the world's mountains: Spatio-temporal patterns and potential controls. PLOS ONE, 17, e0271466. https://doi.org/10.1371/journal.pone.0271466