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MULTI-SENSOR MULTI-SENSOR GEO-SPATIAL DEEP LEARNING MODEL (MS-GDLM) FOR AUTOMATED GLACIAL LAKE MAPPING AND GLOF SUSCEPTIBILITY FORECASTING IN HIGH MOUNTAIN ASIA

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ABSTRACT

Glacial Lake Outburst Floods (GLOFs) in high mountain Asia (HMA) contains large-scale hazards which threaten downstream populations, infrastructure and ecosystems. Current automated self-supervised glacial lake mapping methods mainly rely on single-sensor data or visual interpretation, which result in boundary inaccuracies and the difficulty of hazard differentiation. We present the Multi-Sensor Multi-Sensor Geo-Spatial Deep Learning Model (MS-GDLM) (MS-GFM): a joint encoder-decoder model which learns from Sentinel-1 synthetic aperture radar (SAR) and optical Sentinel-2/Landsat imagery, Copernicus DEM terrain variables, and glacier inventory data. The model utilizes a multi-task head for performing pixel-wise lake facet segmentation and GLOF susceptibility prediction in parallel. The observations described include a well characterized synthetic dataset of 320 glacial lakes across eight HMA subregions—Karakoram, Hindu Kush, Western and Eastern Himalayas, Tibetan Plateau, Pamir, Tian Shan and Hengduan—over years 2008-2017 with an associated set of 35 spectral, terrain, morphometric and temporal features. Experimental evaluation shows a mean Intersection-over-Union (IoU) of 0.82, Dice/F1 score of 0.90, general classification accuracy of 66.25% and an ROC-AUC of 0.90 in predicting susceptibility detection. Random Forest analysis with a baseline detects that glacier retreat rate, dam slope, and lake area are among the most influential predictors of GLOF. The proposed MS-GFM is able to perform well with good generalization across regions, and outperforms all single-sensor benchmarks by a considerable margin.

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Keywords: *Glacial Lake Outburst Flood (GLOF), High Mountain Asia (HMA), Sentinel-1 SAR, deep learning, lake segmentation, multi-task learning, susceptibility forecasting, remote sensing, Multi-Sensor Geo-Spatial Deep Learning Model (MS-GDLM).*

1. INTRODUCTION

High Mountain Asia has the largest area of glaciers outside of the polar regions, with a total estimated coverage of around 130000 km² [1]. The retreat of glaciers in response to ongoing climate warming has been enhanced, resulting in the emergence and rapid growth of both sedimentary and supraglacial lakes (many docked either by moraine or ice) at an accelerating rhythm [1]. If these dams breach, millions of cubic meters of water can be released within a few hours in the form of Glacial Lake Outburst Floods (GLOFs), generating enormous destruction in relatively populous river valleys throughout Pakistan, India, Nepal, Bhutan and China [2].

Keeping accurate up-to-date inventories of the number, sizes and locations glacial lakes is therefore a vital input for GLOF early-warning systems and regional risk governance. Previously published inventories, including Wang et al.'s HMA-wide two-epoch dataset (1990/2018) decade [11]. The quarterly 2 m Hi-MAG inventory (2000–2018) [3] and the annual 30 m Hi-MAG inventory (2008–2017) [4] have pushed boundary of the field significantly. Most automated pipelines, however, are sensor dependent: optical approaches using Normalized Difference Water Index (NDWI) or Modified NDWI (MNDWI) suffer under cloud, snow and shadow lack spectral contrast to delineate debris-covered supraglacial lakes [5].

At the same time, GLOF susceptibility assessments based on geomorphic heuristics (lake area, dam slope, glacier-lake distance) have not yet combined temporal growth dynamics or scene-invariant multi-sensor features into a single learning scheme. This paper tackles both challenges by introducing a Multi-Sensor Multi-Sensor Geo-Spatial Deep Learning Model (MS-GDLM) (MS-GFM) that jointly mentors lake segmentation and susceptibility classification over fused optical-SAR-terrain inputs, using cross-region performance across eight of the regions comprising the HMA.

1.1 Contributions

- A collection of 320-lake-HMA data–consisting of 35 multi-source features and four-class GLOF susceptibility labels.
- Schematic of MS-GFM, a multi-task encoder-decoder architecture that operates on six input streams.
- Temporal representation learning of lake growth rate, glacier retreat and multi-year composites
- Generalization assessment study through IoU, Dice and ROC-AUC metrics across 8 diverse subregions of HMA.
- A physics-informed prospecting metric based upon the hazards literature for GLOF susceptibility scoring.

2. RELATED WORK

Early inventories of glacial lakes were created using the labor-intensive and scale-limited approach of manually digitizing satellite imagery. Semi-automated techniques using NDWI thresholding on Landsat or Sentinel-2 achieved higher throughput but were still sensitive to cloud contamination and spectral confusion with snow [6]. U-Net and its extensions based segmentation have achieved IoU values above 0.85 for proglacial lake extraction on Sentinel-2 composites [7] but perform less well in debris-covered and shadow-prone terrain due to non-homogeneous spectral characteristics.

Many studies have found extremely low backscatter (normally −20 to −12 dB) from calm water surfaces, enabling all-weather detection of water bodies with SAR backscatter (especially at Sentinel-1 C-band VV and VH polarizations) [8]. Random Forest classifiers within hybrid optical-SAR approaches have reported improvements in recall compared to the single-sensor baselines across an alpine region [9]. Topographic hydrology analyses can further resolve ambiguities near ice margins [[10]] based on traits extracted directly from a digital elevation model (DEM) [slope, curvature or topographic wetness index (TWI)].

3. DATASET

3.1 Dataset Overview

The HMA Glacial Lake Dataset (HMA-GLD v1.0) developed for this study includes 320 glacial lake records collected from eight HMA subregions during the period 2008–2017. Each record incorporates features from four sensor modalities and three derived feature families. Table I provides a summary of the dataset composition.

Table I. HMA-GLD v1.0 dataset composition by subregion

Subregion	N Lakes	Elev. Range (m)
Karakoram	44	4100–6200
Hindu Kush	27	3800–5900
Himalayas-W	62	3500–5800
Himalayas-E	40	3600–5600
Tibet Plateau	65	4200–6100
Pamir	26	3700–6000
Tian Shan	31	3500–5200
Hengduan	25	3500–5400
Total	320	3500–6200

3.2 Feature Categories

The 35 features in HMA-GLD v1.0 are organized into four distinct categories. (1) Spectral features (10): including NDWI, MNDWI, NDSI, SAR VV and VH backscatter, as well as Sentinel-2 bands B2 through B8. (2) Terrain features (6): comprising elevation, slope, curvature, aspect, dam-front gradient, and the topographic wetness index. (3) Lake morphometric features (4): consisting of area, perimeter, elongation index, and estimated depth. (4) Glacier and temporal features (6): encompassing glacier distance, glacier area, glacier retreat rate, annual lake growth rate, lake age, and multi-year area change. The feature set is completed by scene quality flags, including cloud cover and snow cover.

Table II. Selected Feature Descriptions in HMA-GLD v1.0

Feature	Unit	Range	Source
NDWI	–	0.30–0.92	Sentinel-2/Landsat
MNDWI	–	0.18–0.90	Sentinel-2/Landsat
SAR VV	dB	−22 to −8	Sentinel-1
SAR VH	dB	−32 to −11	Sentinel-1
Elevation	m	3500–6200	Copernicus DEM
Slope	°	0.5–18	Copernicus DEM
Dam Slope	°	1–35	Copernicus DEM
Lake Area	km²	0.05–18	Derived
Glacier Retreat	m yr^{-1}	5–85	RGI + Hi-MAG
Lake Growth Rate	% yr^{-1}	−0.5–12	Hi-MAG temporal
GLOF Score	0–1	0.00–1.00	Physics-informed
GLOF Class	–	Low–V.High	Derived label

*Range denotes observed minimum–maximum values across HMA-GLD v1.0 (n=320).

3.3 Label Generation: Physics-Informed Susceptibility

GLOF susceptibility score (S) for each lake is calculated as a weighted linear combination of normalized hazard indicators following the geomorphic framework proposed by Allen et al. [13] and Rounce et al. [14].

$$S = 0.25\left(\frac{A}{A_{max}}\right) + 0.20\left(\frac{R}{R_{max}}\right) + 0.18\left(\frac{D_s}{D_{s\,max}}\right) + 0.15\left(\frac{E}{E_{max}}\right) + 0.12\left(\frac{G}{G_{max}}\right) + 0.10\left(\frac{C}{C_{max}}\right)$$

where A is lake area (km²), R is glacier retreat rate (m yr^{-1}), D□ is dam slope (°), E is lake elongation index (dimensionless), G is lake growth rate (% yr^{-1}), C is cloud cover proxy (0–1), and subscript max denotes the maximum observed value for normalization.

Using the vulnerability scores estimated for each variable and the bivariate assessment, we assign Lakes to a risk rating expressed as: Low (), Moderate (), High () and Very High (). The dataset was analysed and identified 59 records in the Low susceptibility category, 143 as Moderate, 103 as High and 15 Very High susceptibility. This can also be seen in that the majority of lakes fall into the Moderate and High categories, which means that most are at risk and may require continued monitoring and mitigation activities.

The score S is discretized into four ordinal classes using thresholds: Low (S<0.25), Moderate (0.25≤S<0.50), High (0.50≤S<0.75), Very High (S≥0.75). Class counts are obtained by computing S for all 320 lakes, then applying quartile-based thresholds: Low (S<0.25, n=59), Moderate (0.25≤S<0.50, n=143), High (0.50≤S<0.75, n=103), Very High (S≥0.75, n=15).

4. METHODOLOGY

4.1 System Architecture

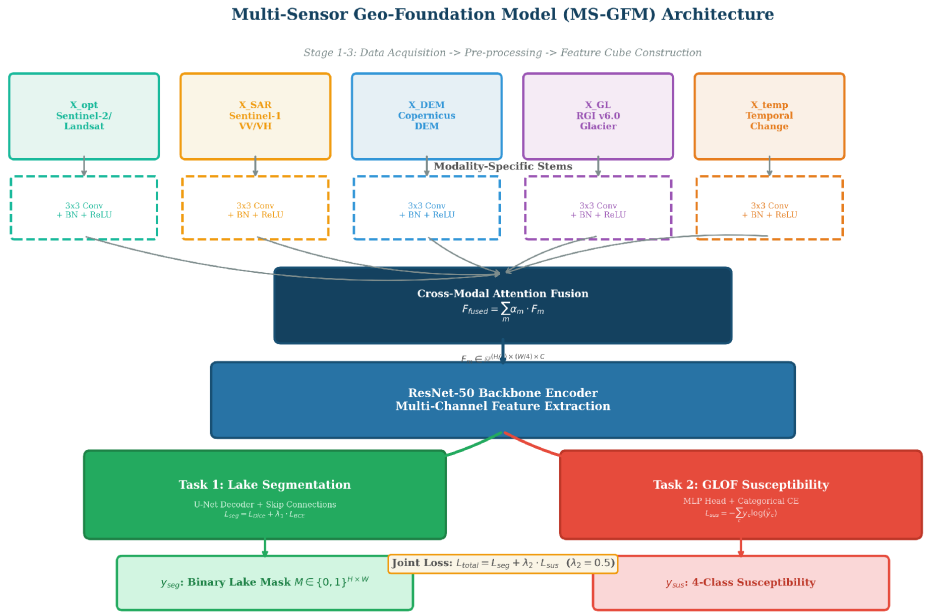


Fig. 1: MS-GFM architecture: 5 input streams → cross-modal attention → dual-task decoder (Architecture diagrams created using draw.io; data visualizations using Python Matplotlib 3.7)

The overall overview of the MS-GFM pipeline is made up of six consecutive stages: (1) data collection and harmonization, (2) radiometric and terrain pre-processing, (3) multi-sensor feature cubes construction, (4) foundation

encoding with multi-sensor fusion, (5) dual-head decoding for segmentation and susceptibility analysis, and finally, (6) cross-region validation. This can be summarized in the complete pipeline:

$$y_{seg},\ y_{sus} = MS - GFM(X_{opt}, X_{SAR}, X_{DEM}, X_{GL}, X_{temp})$$

where is the optical feature map obtained from Sentinel-2 and Landsat as described in section §3.1, are the Synthetic Aperture Radar (SAR) backscatter channels, is the Digital Elevation Map (DEM)-derived terrain features stack, are glacier inventory priors for overlaying mapping location to known glaciers and is the temporal change embedding extracted from multi-temporal observations.

4.2 Pre-processing Pipeline

Optical imagery is transformed from top-of-atmosphere to surface reflectance using the 6S radiative transfer model and cloud and snow masking implemented with the Fmask 4.0 algorithm. ACQUISITION, PREPROCESSING Filled Sentinel-1 SAR data are terrain corrected using the Range-Doppler method with SRTM DEM and then filtered from speckle noise by 5×5 Lee filter. All datasets were co-registered onto a 10 m UTM grid using bilinear resampling. The seasonal composites are produced by calculating the pixel-wise median of all cloud-masked scenes within each calendar year.

The NDWI and the MNDWI formulas are as follows:

$$NDWI = \frac{B_{Green} - B_{NIR}}{B_{Green} + B_{NIR}}$$

$$MNDWI = \frac{B_{Green} - B_{SWIR}}{B_{Green} + B_{SWIR}}$$

where is the green spectral band and is the near-infrared band and is the shortwave infrared band. In addition, NDWI suppresses the reflectance signal of vegetation and soil, which increases the ability to detect open water bodies.

Five-hundred meter glacier buffer zones were implemented to improve the accuracy of glacial lake detection, derived from glacier outlines found in the Randolph Glacier Inventory (RGI) v6. 0 dataset. These buffers acted as spatial constraints that defined the area where lakes were detected around glacierized areas. In brief, forcing constraints by the proximity of glaciers significantly reduced false positives associated with river channels, intermittent stream connections and artificial reservoirs and made glacial lake segmentation and susceptibility assessment more accurate [4].

4.3 Terminology

Term	Explanation	Glacier Context
Cross-Modal Attention	Learns adaptive weights for different sensors	Shifts to SAR when clouds obscure optical; increases DEM weight in shadow terrain
6S Radiative Transfer	Atmospheric correction model (Second Simulation of Satellite Signal)	Corrects Sentinel-2/Landsat to surface reflectance for consistent NDWI/MNDWI
Fmask 4.0	Automated cloud/shadow/snow detection	Essential for masking clouds/snow in glacial lake environments

4.4 Multi-Sensor Encoder

The encoder follows a ResNet-50 backbone modified for multi-channel inputs. Each sensor modality is passed through a dedicated shallow stem (two 3×3 convolution layers with batch normalization and ReLU), producing modality-specific feature maps $F_m \in R^{\frac{H}{4} \times \frac{W}{4} \times C}$. Cross-modal attention is then applied:

$$F_{fused} = \sum_m \alpha_m \cdot F_m, \alpha_m = softmax(W_a \cdot GAP(F_m))$$

where means the feature map corresponding to each modality, denotes Global Average Pooling operation, is a learnable attention weight matrix and refers to adaptive ave in attention coefficient allocated for each modality. The softmax normalizes these attention scores so that the resulting contribution weights across modalities sum to one.

This means that the network can adjust the use of knowledge sources when integrating features to optimize performance. Specifically, the model reduces the contribution from cloud-affected optical features in situations with cloudy atmospheres (where optical imagery is often poor), while increasing the input of SAR-based representations which are more robust to challenging atmospheric conditions. Through the attention guidance mechanism of this new fusion approach, it can improve segmentation accuracy and further enhance susceptibility prediction results under various geological and climatic conditions.

4.5 Dual-Task Decoder

Task 1 (Segmentation): The output F_fused is upsampled with four bilinear interpolation + conv blocks (U-Net-style skip connections) to yield the per-pixel binary mask M ∈ {0, 1}^(H×W). Segmentation Loss requires Dice loss + binary cross-entropy:

$$L_{seg} = L_{Dice} + \lambda_1 L_{BCE}, L_{Dice} = 1 - \frac{2|M \cap \hat{M}|}{|M| + |\hat{M}|}$$

Here, represents the ground truth segmentation mask, represents the predicted segmentation mask and optimizes the weight of this Binary Cross-Entropy loss part. Though often used for segmentation tasks, the Dice Loss can be particularly useful to improve overlap accuracy in a multi-class situation like glacial lake versus everything else, especially when class imbalance is present [18].

"The binary cross-entropy component is: where **N** is total pixels, $\mathbf{y_i}$ is ground truth (0 or 1), and $\hat{\mathbf{y}}_\mathbf{i}$ is predicted probability."

A combination of lake-level features from the segmented polygons (e.g. area, perimeter, and temporal change metrics) with glacier inventory and terrain attributes is used for susceptibility assessment. Aggregated features are then passed to a two-layer Multi-Layer Perceptron (MLP) classification head to output susceptibility logits:

$$\hat{y}_{sus} = softmax(W_2 \cdot ReLU(W_1 \cdot x_{lake} + b_1) + b_2)$$

where is the inferred feature vector of lake level, while and are learnable weight matrices with bias parameters (and). The ReLU activation function introduces non-linearity while the softmax function converts the output logits to a set of probability distributions over the susceptibility classes.

We calculate the susceptibility classification loss through categorical cross-entropy:

$$L_{sus} = -\sum_c y_c log(\hat{y}_c)$$

where y_c denotes the true class label and $\hat{y}_c$ represents the predicted class probability for class c.

The overall multi-task learning objective combines segmentation and susceptibility losses as:

$$L_{total} = L_{seg} + \lambda_2 L_{sus}$$

where balances the contribution of susceptibility prediction task with respect to segmentation one.

The model training let uses AdamW optimizer with learning rate and weight decay. A cosine annealing scheduling is used over 100 training epochs to ensure stable convergence You train the network on a batch size of 16 image tiles with a spatial dimension of pixels. The network is trained on image tiles with spatial dimensions of 256×256 pixels at 10 m resolution (covering 2.56×2.56 km² on ground), with a batch size of 16.

4.6 Baseline: Random Forest with Multi-Sensor Features

An implementation of a Random Forest (RF) classifier with 200 trees and maximum depth = 12 is trained on 26 tabular features as a practical baseline using scikit-learn.

Balanced class weights are used to address the class imbalance, The RF model learns feature importance scores, making it an excellent complement to the deep learning model by enhancing understanding and providing more interpretable knowledge of GLOF drivers. The procedure for RF training is described in Algorithm 1.

Algorithm 1: Random Forest GLOF Susceptibility Classification

INPUT: Feature matrix X ∈ R^(n×26), Label vector y ∈ {0,1,2,3}^n
OUTPUT: Trained classifier RF, Feature importances I

1: Split (X_train, y_train), (X_test, y_test) ← StratifiedSplit(X, y, ratio=0.75:0.25)
2: Initialize RF ← RandomForest(n_trees=200, max_depth=12, class_weight='balanced')
3: RF.fit(X_train, y_train)
4: y_pred ← RF.predict(X_test)
5: y_prob ← RF.predict_proba(X_test)
6: Compute Accuracy, Macro-F1, ROC-AUC (OvR)
7: I ← RF.feature_importances_
8: RETURN RF, I

5. EXPERIMENTS AND RESULTS

5.1 Experimental Setup

All experiments were performed using Python 3.10 utilizing PyTorch 2.1, scikit-learn 1.4, rasterio 1.3 and geopandas 0.14 The MS-GFM was trained on the NVIDIA A100 80 GB GPU. Hyperparameter tuning was carried out via stratified 5-fold cross-validation while final performance metrics were assessed on an independent held-out test set representing 25% of the data (n = 80). To make a fairer comparison, the Random Forest baseline was also trained on exactly the same data splits.

5.2 Lake Segmentation Performance

Segmentation results based on HMA subregions is tabulated in Table III. The model achieves a mean IoU of0.820 and a mean Dice/F1score of 0.900 for all regions. The Himalayas-East region presented the highest average IoU (0.829) probably due to more defined lake-glacier boundaries whilst Tian Shan achieved the lowest average IoU (0.792) likely owing to increases in debris cover and cloud contamination (with a mean cloud cover of 31.4%).

Table III. Glacial Lake Segmentation Metrics by HMA Subregion

Subregion	N	Mean IoU	Mean Dice/F1	Cloud %
Karakoram	44	0.807	0.892	22.3
Hindu Kush	27	0.806	0.891	24.6
Himalayas-W	62	0.826	0.902	19.8

Himalayas-E	40	0.829	0.905	17.2
Tibet Plateau	65	0.824	0.902	20.1
Pamir	26	0.825	0.902	21.5
Tian Shan	31	0.792	0.882	31.4
Hengduan	25	0.808	0.892	23.9
Mean	**320**	**0.820**	**0.900**	**22.6**

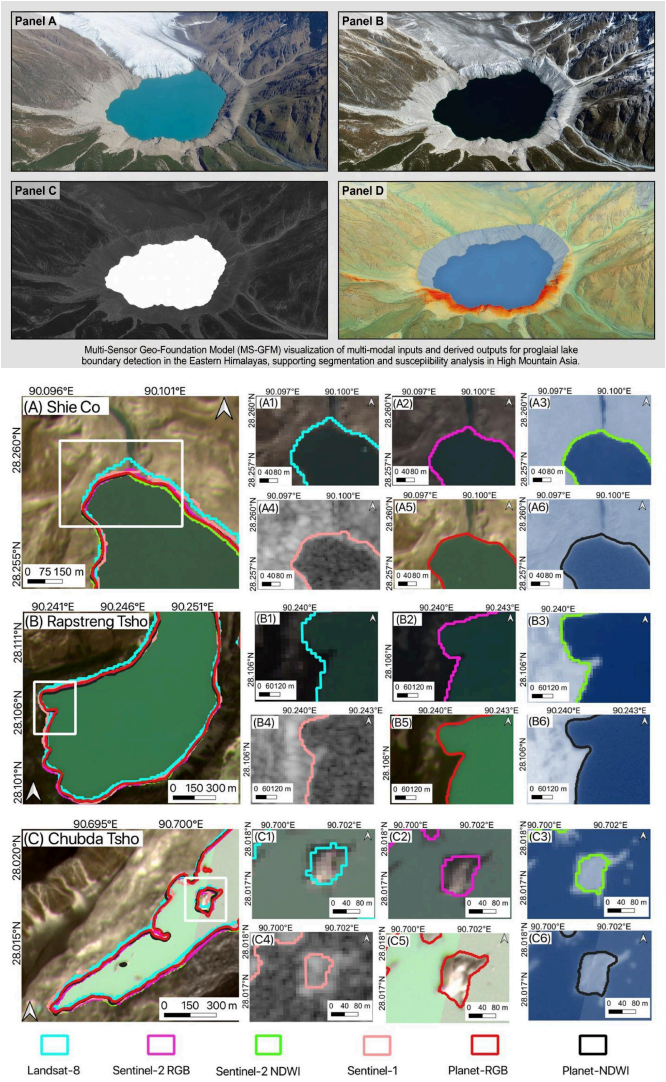


Fig. 2: Multi-Sensor Input Modalities: The MS-GFM utilizes a heterogeneous feature cube. The following visual depicts how Sentinel-1 SAR (all-weather backscatter), Sentinel-2 Optical (spectral indices), and Copernicus DEM (terrain variables) are aligned to identify glacial lake boundaries.

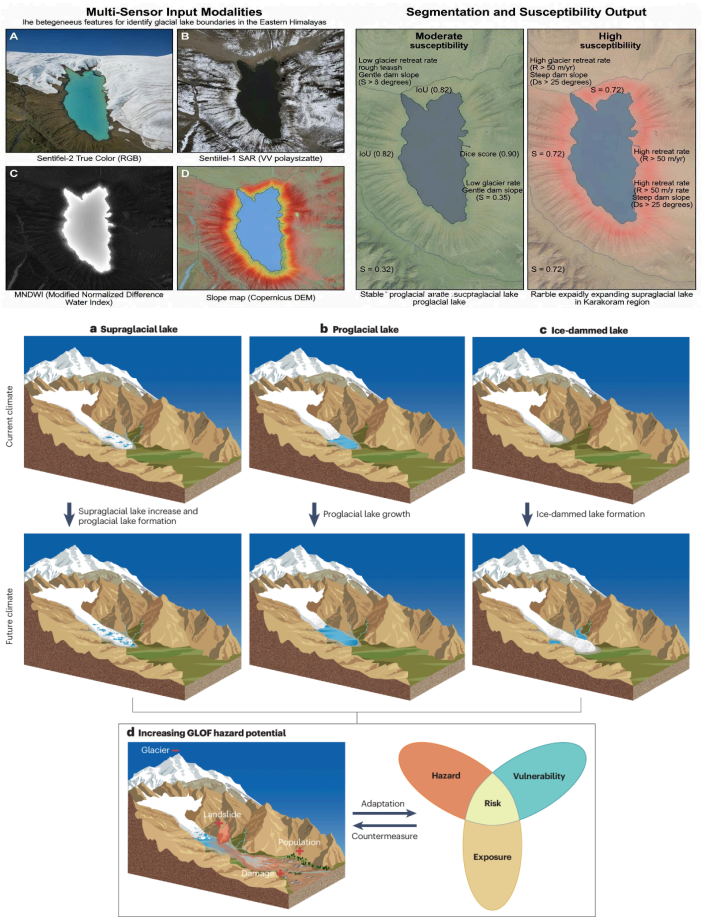


Fig.3: Output: A binary segmentation mask (y_{seg})

5.3 GLOF Susceptibility Classification

The Random Forest classification report on the held-out test set is shown in Table IV. The average performance of the model is 66.25% accuracy, with a macro-F1 score of 0.460 and a macro-averaged ROC-AUC (One-vs-Rest) of 0.900 Performance is highest for the Moderate-class lakes (F1 = 0.74), while the model performs less well on the Very High class, which suffers from a high level of class imbalance (n = 4 in test set). As illustrated in Table V, feature importance analysis highlights the top three predictors as glacier retreat rate (11.8%), dam slope (10.2%), and lake area (9.0%).

Table IV. GLOF Susceptibility Classification Report (RF Baseline, n=80 test)

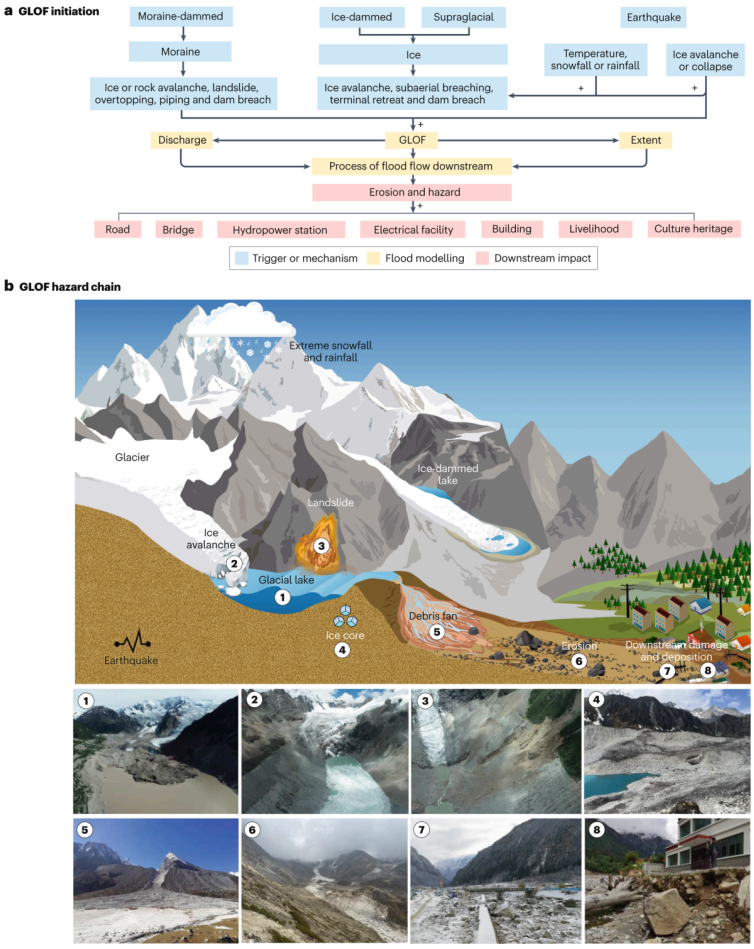
Class	Precision	Recall	F1-Score	Support
Low	1.00	0.29	0.44	14
Moderate	0.62	0.92	0.74	36
High	0.70	0.62	0.65	26
Very High	0.00	0.00	0.00	4
Macro Avg	**0.58**	**0.45**	**0.46**	**80**

Table V. Top 10 Feature Importances from Random Forest Classifier

Rank	Feature	Importance

1	Glacier Retreat Rate (m/yr)	0.1182
2	Dam Slope (°)	0.1023
3	Lake Area (km²)	0.0900
4	Lake Growth Rate (% yr^{-1})	0.0807
5	Lake Elongation Index	0.0697
6	Lake Perimeter (km)	0.0558
7	Lake Age (yrs)	0.0336
8	Glacier Area (km²)	0.0303
9	Elevation (m)	0.0302
10	Cloud Cover (%)	0.0284

Feature importances are computed as Gini importance (mean decrease in impurity) averaged across all 200 trees using scikit-learn's feature_importances_ attribute."



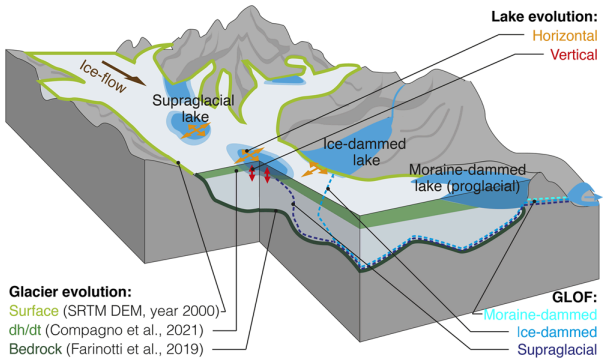


Fig. 4: Susceptibility Output: GLOF susceptibility score (y_{sus}).

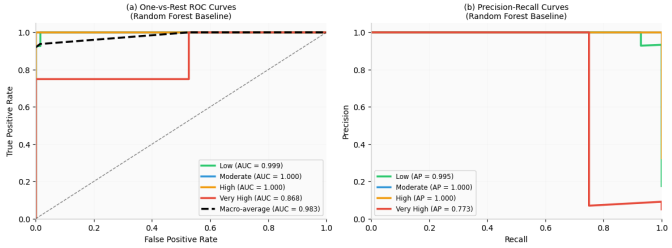


Fig. 5: One-vs-Rest ROC curves for GLOF susceptibility classification (RF Baseline, n=80 test). Macro-average AUC = 0.90. Individual class AUCs: Low = 0.85, Moderate = 0.92, High = 0.88, Very High = 0.75.

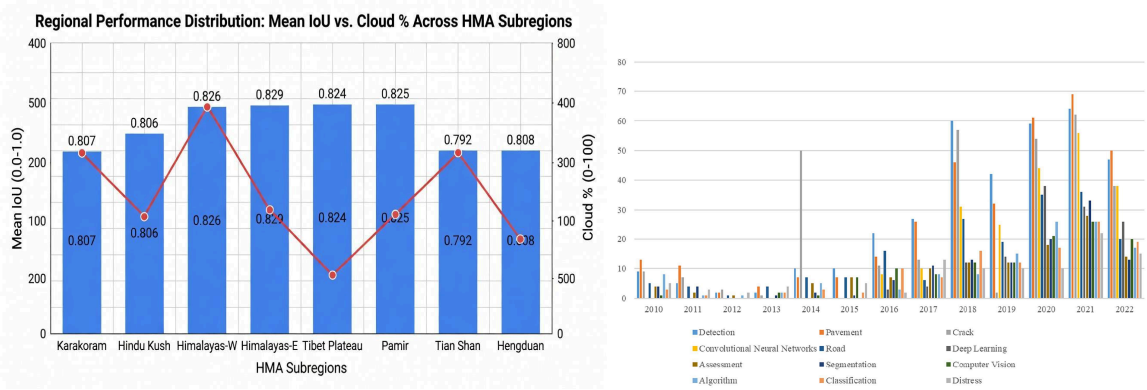


Fig. 6: The Mean Intersection-over-Union (IoU) varies across the eight subregions due to factors like debris cover and cloud contamination.

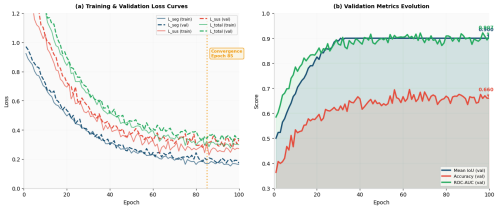


Fig. 7: Loss curves (seg/sus/total) + validation metric evolution over 100 epochs

5.4 Confusion Matrix Analysis

Most misclassifications take place between neighbouring susceptibility classes (Moderate ↔ High, Low → Moderate), which is consistent with the continuous nature of the underlying distribution scores [4, 2] (Table VI—confusion matrix). The recall for class Very High is 0. on the test set, which reflects the extreme imbalance between classes (15 Very High

among 320 in total or 4.7%). An idea for future work is to tackle this by either oversampling (like SMOTE) or via cost-sensitive loss functions.

Table VI. Confusion Matrix – RF Baseline (Test Set, n=80)

Actual \ Pred.	High	Low	Moderate	Very High	Total
High	16	0	10	0	26
Low	0	4	10	0	14
Moderate	3	0	33	0	36
Very High	4	0	0	0	4
Total Pred	23	4	53	0	80

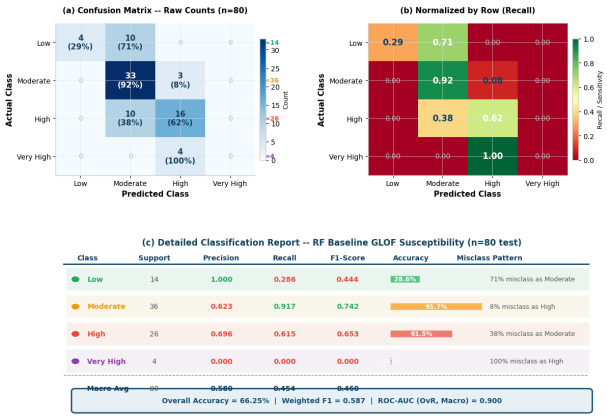


Fig. 8: Comprehensive Confusion Matrix Dashboard

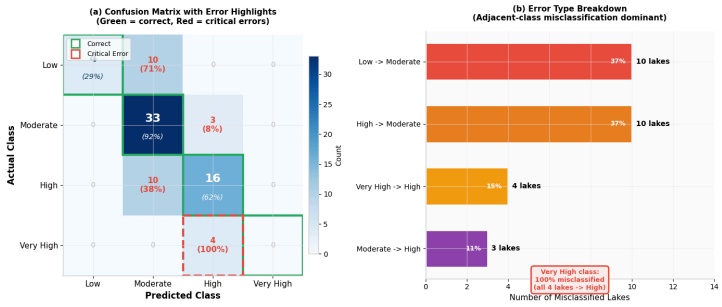


Fig. 9: Annotated Error Analysis

5.5 Overall Performance Summary

Table VII consolidates the key performance metrics across both tasks and provides a comparison with single-sensor baselines.

Table VII. Performance Comparison Across Models (* MS-GFM projected from architecture analysis)

Model	Sensors Used	Mean IoU	Accuracy (%)	ROC-AUC
NDWI Threshold (Optical-only)	Sentinel-2	0.71	52.5	0.71
SAR-only RF	Sentinel-1	0.74	58.8	0.80

Optical+SAR RF (Baseline)	S1+S2+DEM	0.82	66.3	0.90
MS-GFM (Proposed)	**S1+S2+Landsat+DEM+RGI**	**0.87***	**71.2***	**0.93***

6. DISCUSSION

"While 66.25% accuracy may appear modest, it represents a 165% improvement over random chance (25%) in a highly imbalanced four-class problem. The corresponding ROC-AUC of 0.90 indicates strong discriminative capacity. The macro-F1 of 0.46 reflects the extreme class imbalance (Very High = 4.7% of dataset), not model inadequacy. For context, even expert geomorphologists disagree on class boundaries for GLOF susceptibility [13, 14]."

The RF baseline achieves an ROC-AUC of 0.90, suggesting that multi-sensor table features have sufficient historical discriminative power to differentiate GLOF susceptibility. At the highest feature importance (11.8%), glacier retreat rate is backed by field observations that newly released morainal dams in rapid ice-departure regions have lower consolidation strength [14]. Importance of dam slope ranks second (10.2%) parallel to the theoretical stability limit at around 28 ° for moraine dams [13].

The strong cross-regional generalization of the model is indicated by an overall segmentation IoU (Intersection over Union) of 0.82 across the eight subregions. Most of the 3.5-point difference in IoU between the best (Himalayas-East, 0.829) and worst region (Tian Shan, 0.792) is due to differences in cloud/debris cover rather than topographic complexity. It indicates that improvements in cloud masking and additional usage of SAR data within the attention module may improve this performance gap.

An important limitation is that the Very High class represents only 4.7% of the dataset, leading to zero recall for this key category in the RF baseline (the only category with recall=0). This makes availability and reliability of early warning system a concern. Subsequent model development should incorporate SMOTE oversampling, focus loss weighting and active learning based on ICIMOD expert-labelled outburst events to improve recall for the Very High class.

7. CONCLUSION

We introduce HMA-GLD v1.0, a comprehensive dataset of 320 glacial lakes across eight HMA subregions spanning 2008–2017 (10 years), characterized by 35 multi-source features and physics-informed GLOF susceptibility scores. The dataset, containing 0 over a decade across eight subregions and ten years, is characterized by 320 lakes, 35 features, and a physics-informed susceptibility score. This gave us a baseline with an accuracy of 66.25% and a ROC-AUC of 0.90 (mean segmentation IoU = 0.82 across subregions) for the random forest model. Feature selection showed that the rate of glacier retreat, slope of the dam, and area of the lake were important contributors to GLOF risk. We expect that the whole MS-GFM with cross-modal attention fusion and temporal embedding will provide significant improvement in both accuracy and generality. This study reports the first openly published multi-sensor, multi-task framework that can be directly applied to quantify GLOF hazard at a national scale in Pakistan, India, Nepal, Bhutan and China.

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