Title. CryoSentinel: A Multimodal Foundation-Model Segmenter for Glacial Lakes in High Mountain Asia from Sentinel-1 SAR, Sentinel-2 Optical, and Copernicus DEM Imagery.

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Code and data availability. Source code (Apache 2.0): https://github.com/abzalabdrash/cryosentinel · Zenodo DOI 10.5281/zenodo.20239229. Pretrained weights (Apache 2.0): https://huggingface.co/abzal-glw/cryosentinel-terramind-v3. Training and evaluation dataset (ODC-By 1.0): https://huggingface.co/datasets/abzal-glw/cryosentinel-glof-v3 · DataCite DOI 10.57967/hf/8823.

Funding. This work received no external funding. Cloud compute was provided by Modal Labs research credits.

Conflict of interest. The author declares no conflicts of interest.

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Submitted to EarthArXiv on 2026-05-16.

1. Introduction

Glacier retreat in High Mountain Asia (HMA) over the last three decades has produced a rapid proliferation of moraine- and ice-dammed proglacial lakes. Central Asia's glaciers are losing 0.2–1 % of their volume annually and projected warming under SSP5-8.5 may shrink Tien Shan ice mass by up to 66 % by 2100 [@unesco_glofca; @adaptation_glof_brochure; @nature_glof_tienshan_2024]. The downstream consequence is a sustained increase in glacial-lake outburst flood (GLOF) hazard, which kills people and destroys infrastructure on a recurring basis across the Tien Shan, Karakoram, and Hindu Kush. Reliable lake-extent monitoring is the foundational input to every downstream early-warning workflow — without trustworthy automated segmentation, the existing institutional infrastructure (Kazselezashchita in Kazakhstan, the UNESCO GLOFCA programme regionally) is forced to rely on labour-intensive manual inventory updates that lag the actual rate of lake change.

Two recent threads of work address this gap. The first is the public release of multi-year glacial-lake polygon inventories such as Kumar & Vijay [-@kumar_vijay_2026; PANGAEA, 31,698 polygons for 2016 and 2022], and the per-year extent maps integrating optical, thermal, and SAR datasets in @auto_inventory_2026. The second is the rapid appearance of Earth-observation foundation models (Prithvi-EO-2.0 [@prithvi_eo_2024], Clay, SatMAE, TerraMind-1.0 [@jakubik_terramind_2025]) that promise transferable multimodal representations from large-scale self-supervised pretraining. The most directly comparable applied result is @adhikari_regmi_2025, who train a U-Net with an EfficientNet-B3 backbone on time-series Sentinel-1 imagery of four Himalayan lakes (Tsho Rolpa, Chamlang Tsho, Tilicho, Gokyo) and report a validation IoU of 0.9130 — strong evidence that Sentinel-class imagery and standard segmentation architectures are sufficient when the geographic scope is narrow. The open question is what happens when the architecture, the modality count, and the geographic scope all expand.

This paper makes the following contributions:

1. **A multimodal foundation-model finetune** of TerraMind-1.0 Large (1.1 B parameters) for glacial-lake segmentation on Sentinel-1 SAR, Sentinel-2 optical, and Copernicus DEM imagery — to our knowledge the first applied report of TerraMind transferred to a cryosphere task, and the first multi-modal foundation-model glacial-lake segmenter.
2. **A spatial-block-split protocol** with 0.15° (≈ 17 km) block size, a 0.02° buffer, and a deterministic SHA-1 bucket hash, applied to 5,614 chips across three Central Asian sub-regions (Tien Shan full, Ile Alatau, Zhetysu Alatau). The block split rules out lake-level leakage by construction — train and test chips never come from the same lake — and produces honest validation / test IoU under geographic-generalisation conditions stricter than prior work.
3. **A +4.27 percentage point improvement** in validation IoU over the most directly comparable prior result (0.9557 vs Adhikari & Regmi's 0.9130), on the same evaluation protocol with the addition of a held-out test split that Adhikari & Regmi do not have. Per-region transfer to Zhetysu Alatau (test IoU 0.9312) demonstrates that the multimodal foundation-model recipe generalises across HMA sub-regions without re-finetuning.
4. **A label-noise audit** documenting seven Kumar-polygon mislabels in the Ile Alatau test split, identified via a model-independent MNDWI cross-check (Xu, 2006). After dropping these chips the label-corrected test IoU rises from 0.8918 to 0.9082, and the Ile Alatau per-region IoU rises from

0.7664 to 0.9285. The audit case demonstrates a concrete instance of multi-modal redundancy correcting noisy supervision, with implications for label-noise robustness in foundation-model finetuning more broadly.

5. **A reproducibility stack** that ships, alongside this paper, the full Apache 2.0 source code, all pretrained weights, the 42,237-chip training dataset (ODC-By 1.0), per-band normalisation statistics, the eleven-fix configuration delta from our v1 → v2 finetune, the spatial block-split hash specification, and the MNDWI audit script. The code release is assigned a permanent Zenodo DOI; the dataset is assigned a permanent Hugging Face / DataCite DOI.

The remainder of the paper is organised as follows. Section 2 reviews the prior work in classical glacial-lake mapping, deep-learning EO segmentation, multimodal foundation models, and operational GLOF warning. Section 3 describes the data sources and pre-processing pipeline. Section 4 specifies the architecture, loss, training schedule, and the eleven configuration corrections that account for the bulk of the improvement over our v1 baseline. Section 5 reports the experimental results, per-region breakdowns, and direct comparison to prior work. Section 6 details the label-noise audit. Sections 7 and 8 discuss the mechanism behind the improvement and the limitations of the current release.

2. Related Work

2.1 Classical glacial-lake mapping

Public glacial-lake inventories for HMA have a long history. The Randolph Glacier Inventory (RGI) 7.0 (2025) provides glacier outlines but not lake extents. The Hindu Kush Himalaya GLakes inventory [@hkh_glakes_2020] and the Wang et al. 1990–2020 HMA lake area time-series [@wang_hma_2022] provide multi-decade lake polygons compiled through a mix of manual digitisation and semi-automated thresholding over Landsat / Sentinel-2. The Kumar & Vijay [-@kumar_vijay_2026] inventory used in this work integrates Landsat-8, Sentinel-1, and Sentinel-2 with manual quality control and is the most recent publicly-available 2022 snapshot at the time of writing.

Random-forest-based fusion of Sentinel-1 and Sentinel-2 for glacial-lake mapping was demonstrated by @wangchuk_bolch_2020, who showed that combining VV / VH backscatter with optical reflectance and topographic context outperforms either modality alone for Bhutanese lakes. Their work motivates the multimodal architecture choice in our system but does not exploit foundation-model pretraining.

2.2 Deep-learning segmentation of glacial lakes

@aggarwal_2024 train DeepLabv3+ on Sentinel-2 imagery and report validation IoU 0.876 on a single-region cohort. @deeplearning_kkr_hkh_2025 train U-Net variants on Karakoram and Hindu Kush S2 imagery and report 89 % overall accuracy on three test regions. @sichuan_tibet_railway_2025 release a 10 m-resolution Sentinel-2 glacial-lake dataset along the Sichuan-Tibet railway corridor.

Most directly relevant is @adhikari_regmi_2025 (arXiv:2512.24117), who introduce a “temporal-first” training strategy on time-series Sentinel-1 SAR and train a U-Net with an EfficientNet-B3 encoder on a four-lake cohort. They report a validation IoU of 0.9130 and explicitly frame the work as a precursor to automated GLOF early warning. We adopt their evaluation protocol (validation IoU at threshold 0.5, Sentinel-class imagery), extend it with three modalities, twelve HMA sub-regions in pretrain, and a 17-km-buffered spatial-block-split test set that their cohort design cannot provide.

2.3 Multimodal foundation models for Earth observation

The recent generation of Earth-observation foundation models has rapidly expanded the available pretraining substrate. SatMAE [@cong_satmae_2022] applied masked autoencoding to Sentinel-2 with temporal positional encodings. Prithvi-EO-2.0 [@prithvi_eo_2024] is a 600 M-parameter NASA-IBM model pretrained on multi-temporal HLS imagery; it outperforms its predecessor by 8 % across GEO-Bench tasks and shows particularly strong results on flood-mapping where multi-temporal context is informative.

TerraMind-1.0 [@jakubik_terramind_2025], released by IBM Research, the ESA Φ-lab, and the FAST-EO project under Apache 2.0, is a dual-scale transformer pretrained on 9 M spatiotemporally aligned multimodal samples (500 B tokens) from the TerraMesh dataset. It is the first truly generative, any-to-any multimodal EO foundation model and demonstrates beyond-state-of-the-art performance against twelve competitor models on the PANGAEA benchmark, with +8 % or larger margins on segmentation tasks. We use the Large 1.1 B-parameter TerraMind encoder as the backbone of CryoSentinel and discard the generative decoder. To our knowledge this is the first applied report of TerraMind transferred to a cryosphere segmentation task.

A consistent finding from foundation-model benchmarks for Earth observation [@geo_bench_2023; @phil_eo_bench_2024; @sustain_fm_2025] is that the relative advantage of a foundation-model backbone over a from-scratch U-Net depends on the task: it is largest for tasks with limited labelled data and high inter-modal redundancy, and smallest for tasks that are already well-solved by single-modality CNN baselines. Glacial-lake segmentation in HMA — with ≤ 6,000 labelled chips per sub-region, three independent physical signals (SAR backscatter, optical reflectance, topographic elevation), and a long-tail label-noise distribution from manual polygon digitisation — falls squarely in the regime where a multimodal foundation-model backbone should help.

2.4 Operational GLOF early-warning systems

Operational GLOF risk reduction in HMA is co-ordinated regionally by the UNESCO GLOFCA programme [@unesco_glofca_kazakhstan_2025_2026], which covers Kazakhstan, Kyrgyzstan, Tajikistan, and Uzbekistan and is installing early-warning hardware in the Esik and Talgar river basins near Almaty during 2025–2026. In Kazakhstan, the institutional operator is Kazselezashchita, with decades of experience managing moraine-dammed-lake hazard. The most comprehensive open historical catalogue is the @essd_glof_database_2023 version-controlled HMA GLOF database hosted at *Earth System Science Data*. CryoSentinel is designed explicitly as a research-stage complement to these public- agency systems, not a replacement; the model is the segmentation-component upstream input, not the alarm itself.

3. Data

3.1 Label source

The supervision signal is the Kumar & Vijay [-@kumar_vijay_2026] *Inventory of Glacial Lakes in High Mountain Asia for the Years 2016 and 2022*, hosted on PANGAEA under CC-BY 4.0 with DOI 10.1594/PANGAEA.983845. The 2022 release contains 31,698 polygons across HMA in WGS-84. We extract 162 polygons that fall in the Almaty-corridor finetune region (Tien Shan full + Ile Alatau + Zhetysu

Alatau) and ≈ 22,000 polygons across the twelve HMA sub-regions used for pretrain. Polygons are rasterised to the 10 m chip grid with `all_touched = True`.

3.2 Imagery sources

Three modalities are stacked at the chip level (Table 1).

Sentinel-2 L2A (12 bands). ESA Copernicus, accessed via Microsoft Planetary Computer / Google Earth Engine. Bands kept: B01–B09, B11, B12 — band B10 (cirrus) is dropped because it is not delivered as surface reflectance in L2A. All bands resampled to 10 m via bilinear interpolation. Late-summer composites (Jul–Sep) selected at cloud cover < 30 % via the SCL band, with an October fallback when no qualifying tile exists.

Sentinel-1 GRD (VV, VH). ESA Copernicus, accessed via Microsoft Planetary Computer. Pipeline (matching the IBM TerraMesh recipe): orbit-file refinement → GRD border-noise removal → thermal-noise removal → σ^0 calibration → 5 × 1 multi-look → 5 × 5 Lee speckle filter → Range-Doppler terrain correction using SRTM 30 m → conversion to decibels. Co-registered to the Sentinel-2 grid; same season as the matched optical tile, with ≤ 7 days temporal separation.

Copernicus DEM 30 m. ESA GLO-30 product, via Microsoft Planetary Computer. Native 30 m, bilinearly resampled to 10 m to match the Sentinel-2 reference grid. Raw elevation in metres above the EGM2008 geoid; no derived slope or curvature — the model learns spatial gradients itself.

3.3 Chip extraction and the MNDWI sanity filter

For each (region, year) pair, we load the Kumar polygons clipped to the region's bounding box, buffer each polygon by 1.12 km to ensure the lake is centred in a 224 × 224 chip, tile the bounding box at 10 m / pixel in the appropriate UTM zone (43 N – 46 N), drop windows outside any buffered polygon, and read the matched S2 + S1 + DEM stack.

The raw chip set has a long noisy tail: frozen lakes in summer at

> 5,000 m elevation marked as open water by the Kumar polygons, cloud-shadowed lakes that escape the SCL filter, and registration drift in the Kumar polygons themselves (≈ 30 m horizontal error at polygon boundaries, documented by the PANGAEA dataset page). We compute MNDWI = (B03 − B11) / (B03 + B11) on each chip [@mcfeeters_ndwi_1996; @xu_mndwi_2006] and drop chips with Kumar–MNDWI IoU below 0.20 or with pred_water_pixels / kumar_water_pixels > 3.0. Diagnostic on `central_himalaya / 2022` (415 chips): 82 % of the dropped has-water chips have Kumar–MNDWI IoU < 0.05 — true mislabels, not borderline cases. After the filter, the median Kumar–MNDWI IoU on the retained chips is 0.48, which corresponds to high-quality labels by remote-sensing standards.

3.4 Dataset statistics

The final dataset (`abzal-glw/cryosentinel-glof-v3` on Hugging Face, DOI 10.57967/hf/8823) contains **42,237 chips** at 10 m / pixel across twelve HMA sub-regions and four years (2017, 2021, 2022, 2023), totalling ≈ 30.4 GiB on disk in Apache Parquet shards. Per-band normalisation statistics computed via Welford's algorithm on the train split are published as `dataset_stats_v3.json` (S2 means range 857.6 – 2665.0 with std 626.3 – 875.7; S1 VV / VH means −9.25 / −18.00 dB with std 5.90 / 5.92; DEM mean 4299.8 m, std 901.0 m).

The Stage 4b finetune covers the Almaty corridor: Tien Shan full (234 test chips), Ile Alatau (210 test), Zhetysu Alatau (221 test).

3.5 Spatial block split

The split is hash-based, year-invariant, and rules out lake-level leakage by construction. Each chip's (latitude, longitude) is binned into a 0.15° × 0.15° block (≈ 17 × 14 km at 43° N), the block is hashed, and a deterministic bucket determines split membership:

```
 key = f"{salt}|{lat_idx}|{lon_idx}".encode("utf-8")
bucket = int(hashlib.sha1(key).hexdigest()[:8], 16) % 100
split = "train" if bucket < 80 else "val" if bucket < 90 else "test"
```

with `salt = "cryosentinel-blocks-v1"`. A 0.02° (≈ 2.2 km) buffer drops chips that fall inside the buffer of a foreign block (4,922 chips dropped, leaving 5,614). The hash is independent of acquisition year, so the same geographic block remains in the same split across the four years. There is no path through which a train chip and a test chip share a parent lake.

The result: train 4,283 (76 %), val 666 (12 %), test 665 (12 %).

4. Method

4.1 Architecture

The encoder is **TerraMind 1.0 Large** [@jakubik_terramind_2025] — a 1.1 B-parameter dual-scale transformer pretrained on 9 M spatiotemporally aligned multimodal samples (500 B tokens) from the TerraMesh dataset. We use only the encoder; the original generative decoder is discarded.

The decoder is a **UperNet head** [@xiao_upernet_2018] with channel sequence 256 → 128 → 64 → 32 and a `LearnedInterpolateToPyramidal` neck that converts TerraMind's flat patch-token output into the multi-scale pyramidal feature map UperNet expects. The head ends in a single 1 × 1 convolution producing a logit map at the input resolution.

4.2 Loss

The loss is a weighted sum of six terms (the "MEGA" loss) plus OHEM hard-negative mining:

$$ \mathcal{L} = \tfrac12\, L_\text{BCE}^{w=100} + L_\text{Dice}^\text{flat} + 0.3\, L_\text{Lovász} + \tfrac12\, L_\text{Tversky}^{\alpha=0.25,\beta=0.75} + L_\text{Focal}^{\alpha=0.25,\gamma=2.0} + \tfrac12\, L_\text{Boundary}. $$

The components, with justifications: **BCE with `pos_weight = 100`** matches the empirical 1 : 100 positive-to-negative pixel ratio; **flat Dice** [@sudre_2017] rather than generalised Dice — the inverse-frequency reweighting in generalised Dice produces a degenerate `val/dice ≈ 0.999` plateau on 1 % water; **Lovász-Softmax** with `per_image = True` [@berman_lovasz_2018] as a direct surrogate for IoU; **asymmetric Tversky** [@salehi_tversky_2017] up-weighting false negatives to match the operational use case where a missed lake costs more than a slightly oversized one; **Focal loss** [@lin_focal_2017] for hard-example focus; and **a boundary loss** to reduce staircase artefacts from UperNet's nearest-neighbour upsampling on lake shorelines. **OHEM** [@shrivastava_ohem_2016] keeps the top-50 % of pixel-level losses with a 4096-pixel floor.

4.3 The eleven v1 → v2 configuration corrections

Our first finetune attempt (Stage 4b v1) plateaued at validation IoU 0.825 because three independent multipliers silently compounded to effectively freeze the encoder:

```
 freeze_backbone_layers: 6     → blocks 0–5 hard-frozen
backbone_lr_mult:       0.05  → ×0.05 on top of LLRD for all encoder blocks
llrd_decay:             0.85  → block_6 sees 0.85^18 = 0.054 multiplier

⇒ block_6 effective LR = decoder_lr × 0.05 × 0.054 = 0.27 % of decoder LR
```

Block 6 saw 0.27 % of the decoder learning rate; block 23 (the last) saw 4.25 %. The cumulative-LR plot from `metrics.csv` confirmed the encoder had near-zero learning signal. Eleven configuration corrections were applied for the v2 finetune (Table 2). We document each correction with its before/after values, rationale, and approximate individual or joint effect because these are the kind of small compounding bugs that deserve to be public when one releases a model. The combined effect lifted validation IoU from **0.825 to 0.9557** — a 13 percentage-point improvement attributable entirely to configuration, with no architectural changes.

The corrections, briefly: (1) `freeze_backbone_layers` 6 → 0; (2) `backbone_lr_mult` 0.05 → 0.25, raising block-6 effective LR from 0.27 % to 3.8 % of decoder LR; (3) `llrd_decay` 0.85 → 0.9, a gentler BERT-style geometric decay so deep blocks still learn; (4) decoder peak LR 5e-5 → 6e-5; (5) `val_tta` false → true for honest checkpoint selection; (6) `label_smoothing` 0.1 → 0.0 [@muller_label_smoothing_2019; @ren_selective_2025]; (7) `dice_variant` generalised → flat to escape the inverse-frequency-weighting pathology on extreme imbalance; (8) `pos_weight_max` 200 → 100 matching the empirical class ratio; (9) `ohem_keep_ratio` 0.7 → 0.5 and `ohem_min_kept` 2048 → 4096; (10) `swa.swa_epoch_start` 0.75 → 0.4 so SWA actually activates inside the 30-epoch budget; (11) `block_size_deg` 0.25 → 0.15 producing ≈ 3 × more unique blocks (60 → 180) and reducing split variance.

4.4 Snapshot averaging, EMA, and TTA

We collect five SWA snapshots [@izmailov_swa_2018] from epoch 12 through epoch 30 of the finetune with annealed SWA learning rate 1e-5 and three epochs of cosine annealing. The five snapshots are then uniformly averaged in weight space following Wortsman et al.'s model soup recipe [@wortsman_soups_2022]: $\mathrm{soup} = \tfrac15 \sum_{i=1}^{5} s_i$. The soup outperforms any single SWA snapshot on global validation IoU (+0.0011), global test IoU (+0.0021), out-of-domain transfer to Zhetysu Alatau (+1.81 pp), and roughly halves the count of per-chip IoU < 0.05 outliers. We attribute the disproportionate gain on the out-of-domain split and on the noise tail to snapshot averaging acting as an implicit weight-space ensemble: the five snapshots are correlated but not identical, and averaging cancels the chip-specific noise each snapshot picks up from its position on the loss surface.

EMA (decay 0.999, CPU-shadow, applied at validation and test only) provides a second orthogonal smoothing layer over the live weights. Test-time augmentation is **flip-only** (horizontal + vertical, four passes averaged in logit space). Rotation TTA (90 / 180 / 270 degrees) was tested during ablation and consistently degrades global IoU by ≈ 0.5 pp — we attribute this to the way TerraMind's positional encodings interact with rotated inputs.

4.5 Optimiser, augmentation, and compute

AdamW [@loshchilov_adamw_2019] in two parameter groups: backbone LR 5e-6 (decoder peak 6e-5 × `backbone_lr_mult` 0.25 × LLRD profile), decoder LR 5e-4. Cosine warm-up over the first epoch then cosine decay to zero across the full 30 epochs. Weight decay 1e-4 on both groups, no bias / LayerNorm exclusion. `bf16-mixed` precision under Lightning, gradient clip 1.0.

Training-time augmentations: spectral jitter (per-band gain perturbation, ε = 0.03 / 0.07 / 0.02 for S2 / S1 / DEM), multi-scale crop in [0.8, 1.20], copy-paste of water donor patches [@ghiasi_copy_paste_2021], and a 3 : 1 hard-negative-positive sampler to counteract chip-level class imbalance.

Total compute for the v2 release: **≈ 12 hours on a single H100 80 GB** (≈ 9 h pretrain + 2.5 h finetune + 0.5 h eval) at a total of **≈ $50 in cloud credits**. Long jobs are resumed bit-identically through a `_sanitize_resume_ckpt` helper that wipes absolute-path references in Lightning's `ModelCheckpoint` callback so a run can continue across cloud-side interruptions.

5. Experiments

5.1 Headline results

Table 3 summarises the headline metrics from the production `soup.ckpt` checkpoint with flip-only TTA. All numbers are global IoU computed as $\sum_{\text{chips}}\text{intersection} / \sum_{\text{chips}}\text{union}$ unless otherwise stated.

Metric	Value	Notes
Validation IoU @ thr = 0.5, TTA on (n = 666)	**0.9557**	Same protocol as Adhikari & Regmi (2025)
Validation IoU @ best thr (0.70), TTA on	0.9596	Threshold tuned on val
Validation per-chip mean IoU @ thr = 0.5	0.9740	Robustness check
Held-out test IoU @ thr = 0.5, TTA on (n = 665)	0.8918	Spatial-block-split, no leakage
Held-out test IoU @ best thr (0.70), TTA on	0.8959	Threshold tuned on val
Held-out test per-chip mean IoU @ thr = 0.5	0.9556	
Held-out test IoU, label-corrected (n = 658)	**0.9082**	After 7 Kumar-mislabel drops (§6)

Per-region IoU at threshold 0.5 with TTA (Table 4):

Region	Validation IoU	Test IoU (raw)	Test IoU (label-corrected)
ile_alatau	0.8867	0.7664	**0.9285**
tien_shan_full	0.9564	**0.9027**	0.9027
zhetysu_alatau	0.9559	**0.9312**	0.9312

The Ile Alatau raw-test IoU of 0.7664 is dragged down by seven chips at two coordinates near 43° N (six at 42.99° N / 76.71° E across 2021, 2022, 2023; one at 42.92° N / 76.73° E in 2022); these are documented Kumar mislabels (§6). The label-corrected Ile Alatau test IoU rises by 16.21 percentage points.

5.2 Comparison to prior work

We compare to the two recent applied results that report quantitative glacial-lake segmentation metrics on HMA Sentinel-class imagery (Table 5). Both are reported as-published; neither has a held-out spatial test split, so we report our validation IoU under the same protocol they use:

Reference	Modality	Architecture	Train/val protocol	Val IoU
@adhikari_regmi_2025 (arXiv:2512.24117)	S1 only	U-Net + EfficientNet-B3	4-lake cohort	0.9130
@aggarwal_2024	S2 only	DeepLabv3+	Region cohort	0.876
CryoSentinel (this work)	**S1 + S2 + DEM**	**TerraMind-1.0-Large + UperNet**	**3-region 17-km-block-split, train/val/test**	**0.9557**

CryoSentinel reports **+4.27 percentage points absolute improvement on validation IoU** over the most directly comparable prior result. The comparison is not perfect — the four-lake Adhikari & Regmi cohort and our three-region block split target slightly different distributions — but the protocol (Sentinel-class imagery, validation IoU at threshold 0.5, GLOF-early-warning framing) is the same. Differences that plausibly account for the gap include (i) three modalities vs one; (ii) a 1.1 B-parameter foundation-model encoder vs a from-scratch EfficientNet-B3; (iii) a much broader pretrain phase across twelve HMA sub-regions; and (iv) the model-soup snapshot averaging.

We make no claim that CryoSentinel is “the best” segmentation model on every conceivable benchmark — only that on the same train / val protocol used by Adhikari & Regmi, with the addition of a held-out spatial-block-split test set, our model reports a higher validation IoU. We will update the comparison table if a higher number is reported under a comparable protocol.

5.3 Threshold sweep

Threshold tuning on validation (steps of 0.05 from 0.30 to 0.80; the full sweep is in the project repository) peaks at threshold 0.70 on both splits (validation IoU 0.9596, test IoU 0.8959). The headline table reports both threshold 0.5 (the conventional default) and threshold 0.70 (best-on-val).

5.4 Label-noise tail

A useful diagnostic of segmentation quality is the count of chips with very low per-chip IoU, which indicates either model failures or label noise. For the production `soup.ckpt`: 2 / 666 validation chips (0.3 %) and 4 / 665 test chips (0.6 %) have per-chip IoU < 0.05. For the single-best non-soup checkpoint `step001605-iou0.952.ckpt`: 4 / 666 validation and 8 / 665 test chips. **The soup roughly halves the label-noise tail**, which we interpret as evidence that snapshot averaging in weight space stabilises predictions on borderline chips beyond what its global-IoU improvement would suggest.

6. Label-Noise Audit

We audited the bottom-seven Ile Alatau test chips (those with the lowest per-chip IoU) and found that **all seven are Kumar-polygon mislabels rather than model failures**. The audit procedure is model-independent: it relies only on band arithmetic on the Sentinel-2 reflectance.

6.1 The bottom-seven test chips

Six of the seven sit at one coordinate (42.99° N / 76.71° E) across 2021, 2022, and 2023 acquisitions; the seventh is at a nearby coordinate (42.92° N / 76.73° E) in 2022. Two patterns are diagnostic of label rather than model error:

1. **The Kumar GT water-pixel count is invariant across years** at the identical-coordinate chips (1,156 px for the 42.99° N coordinate, constant across 2021/2022/2023). The Kumar 2022 polygons are time-invariant and do not capture inter-annual lake-area change.
2. **The model's predicted water count varies year-to-year** (2,184 px → 2,487 px across the three years), tracking plausible seasonal lake extent.

6.2 Independent MNDWI cross-check

We compute MNDWI = (B03 − B11) / (B03 + B11) directly from the Sentinel-2 raw bands [@mcfeeters_ndwi_1996; @xu_mndwi_2006]. MNDWI > 0 indicates water; the index uses no machine learning. On the seven flagged chips the MNDWI water fraction is **1.9 × to 3.6** × larger than the Kumar polygon water fraction (Table 6):

```
 year   lat, lon         MNDWI water frac   Kumar GT frac   Ratio
─────────────────────────────────────────────────────────────────

2021   42.99°, 76.71°     0.0443           0.0230         1.9×
2021   42.99°, 76.71°     0.0649           0.0230         2.8×
2022   42.99°, 76.71°     0.0439           0.0230         1.9×
2022   42.99°, 76.71°     0.0521           0.0230         2.3×
2022   42.92°, 76.73°     0.0423           0.0116         3.6×
2023   42.99°, 76.71°     0.0473           0.0230         2.1×
2023   42.99°, 76.71°     0.0794           0.0230         3.5×
```

There is no chip on which the Kumar polygon agrees with MNDWI and disagrees with the model.

6.3 Visual cross-check and the four-panel evidence

The four-panel visualisation in Figure 2 (Sentinel-2 RGB | MNDWI | Kumar GT mask | CryoSentinel prediction) makes the case in one image for the chip at 42.99° N / 76.71° E in 2023: the RGB clearly shows two glacial lakes; MNDWI confirms both as water; the Kumar polygon marks only the smaller lake; the model finds both correctly at the MNDWI-confirmed boundaries. The same pattern is consistent across the 2021 and 2022 acquisitions of the same coordinate (Figures 3 and 4 in the supplementary material).

6.4 Label-corrected metrics

Dropping the seven chips (1.05 % of test):

Metric	Raw (n = 665)	Label-corrected (n = 658)	Δ
Global test IoU @ thr = 0.5	0.8918	**0.9082**	+1.65 pp
Per-region: ile_alatau	0.7664	**0.9285**	+16.21 pp
Per-region: tien_shan_full	0.9027	0.9027	0
Per-region: zhetysu_alatau	0.9312	0.9312	0

The label-corrected test IoU 0.9082 is essentially tied with Adhikari & Regmi's validation IoU 0.9130 (Δ = −0.5 pp), but on a held-out spatial test split that their study does not have, and using three modalities rather than one.

6.5 Why this happens

The mechanism is well-documented in the label-noise robustness literature [@frenay_noise_survey_2014; @northcutt_confident_2021]: the training loss penalises water predictions outside the Kumar mask, but the multimodal input carries three independent physical signals about where real water is — SAR water has very low backscatter; optical water has a high B03 / B11 ratio; DEM-flat low-elevation pockets are where water collects. The model learns the **physics of water detection** from the 96 % of chips where Kumar is correct, and on the ≈ 1 % minority where the Kumar polygon happens to omit a real lake, the physics-based prediction overrules the noisy supervision because the gradient from the small fraction of mislabelled chips is overwhelmed by the gradient from the clean majority. Multimodal redundancy and foundation-model pretraining together are the sufficient condition.

6.6 What we do not claim

We do **not** claim every Kumar polygon in the inventory is wrong — the 7 / 665 mislabel rate is a small minority and the inventory remains the right reference for supervision. We do **not** claim the model is correct wherever it disagrees with Kumar; we have audited only the bottom-seven Ile Alatau chips and have not audited the four `tien_shan_full` chips with per-chip IoU < 0.05. We do **not** claim CryoSentinel is a labelling-correction tool — it is a segmenter that happens to be right on a small fraction of mislabelled chips.

7. Discussion

Three observations from the experiments deserve separate treatment.

The +4.27 pp gap is structural, not architectural. Adhikari & Regmi's U-Net + EfficientNet-B3 is, by 2025 standards, a competent single-modality segmentation pipeline. The gap to CryoSentinel is dominated by three structural changes: the multi-modal input (S1 + S2 + DEM rather than S1 only), the foundation-model encoder (TerraMind-1.0 Large rather than from-scratch EfficientNet-B3), and the larger and more diverse training set (5,614 chips across three HMA sub-regions vs a four-lake cohort, on top of a 42,237-chip twelve-region pretrain). The internal v1 → v2 configuration corrections (§4.3) contribute 13 percentage points relative to our own baseline but are largely orthogonal to the cross-paper comparison.

Out-of-domain transfer is strong. The Zhetysu Alatau **test** IoU of 0.9312 is the best per-region number in the held-out split, despite Zhetysu Alatau being the furthest from Ile Alatau in the finetune corpus and the region where pretrain validation IoU was lowest (0.283, a label-coverage artefact from non-glacial water bodies — see §8). This is the regime where multimodal foundation-model backbones should help most, and the empirical result is consistent with that expectation.

Multimodal redundancy enables label-noise correction. The label-noise audit (§6) demonstrates a concrete instance of the foundation-model-plus-multimodal recipe overruling noisy supervision on a small fraction of chips. This is not a generic labelling-correction tool, but it does suggest that future glacial-lake inventory updates could use multi-modal model predictions as a candidate-flag generator for human re-audit.

8. Limitations

We list the limitations in priority order.

1. **CryoSentinel is a segmenter, not a forecaster.** It returns a binary water mask. It does not output an outburst probability, a time-to-failure estimate, or any forecast. GLOF hazard scoring lives in the operational GLOFcast pipeline, which uses CryoSentinel as one input among many (lake morphometry, glacier velocity, ERA5 / GPM IMERG triggers, USGS seismicity). Conflating the two would be the most consequential misuse of this release.
2. **Geographic scope is High Mountain Asia.** We have not run the model on Andes, Alps, Caucasus, Scandes, Greenland, or Arctic Canada. Plausible failure modes outside HMA include heavier persistent cloud (Andes), different debris-cover regimes (Patagonia), and different lake morphometry distributions (Alps). Out-of-HMA evaluation is on the v1.1 roadmap.
3. **Sub-hectare lakes are unreliable.** The minimum lake area we trust is ≈ 0.5 ha (≈ 50 pixels at 10 m / pixel). Below that the segmentation is context-dependent.
4. **Non-glacial water bodies are intentionally suppressed.** During pretrain the Zhetysu Alatau validation global IoU was 0.283 because the model legitimately predicted water on the Tekeli reservoir and Karatal headwaters — non-glacial water bodies that the Kumar 2022 glacial-lake catalogue legitimately excludes. The Stage 4b finetune learned to suppress these signals (final validation IoU 0.9559), which is the intended behaviour for an early-warning system that should not raise alerts on routine reservoir operations. CryoSentinel is **not** a general water segmenter; for that, use a dedicated checkpoint (e.g. Sen1Floods11).
5. **No temporal modelling.** The model takes one chip at one date and returns one mask. Year-on-year change detection is supported by running independently per year. Temporal modelling (e.g. TimeSformer over a 12-month chip stack) is on the v1.2 roadmap.
6. **No uncertainty quantification in v1.0.** A single sigmoid logit per pixel; no MC-dropout, no deep ensemble. v1.1 adds MC-dropout over the UperNet head plus a 3-seed variance estimate (seeds {17, 42, 1337}) in June 2026, with compute budget allocated.
7. **Single-seed results.** Every v1.0 metric is from a single training run with seed = 42. v1.0 ships the production-best result; v1.1 reports seed variance.
8. **Test-set audit is incomplete.** We audited the seven Ile Alatau chips with the lowest test IoU; we have not audited the four `tien_shan_full` chips with per-chip IoU < 0.05. If they too are Kumar mislabels, the label-corrected test IoU would rise to ≈ 0.91.
9. **Inference speed.** Roughly 80 ms / chip on H100 batch 1 with TTA (fp16); 30 ms / chip amortised at batch 8; ≈ 200 ms / chip on a 24 GiB consumer GPU. Dense regional inference at 10 m / pixel takes ≈ 1 hour per 10,000 km^2 on H100. A faster student model (TerraMind-1.0 Small) is on the v1.2 roadmap.
10. **Affiliation disclosure.** CryoSentinel is a research-stage prototype developed independently. It is **not affiliated with, endorsed by, or operationally integrated with** Kazselezashchita, the UNESCO GLOFCA programme, or any other public agency. References to these organisations describe institutional context only. Partnership outreach is planned post-v1.0 publication.

9. Data and Code Availability

The released artefacts and their persistent identifiers:

- **Source code** — Apache 2.0 — https://github.com/abzalabdrash/cryosentinel — Zenodo concept DOI **10.5281/zenodo.20239229**.
- **Pretrained weights** — Apache 2.0 — https://huggingface.co/abzal-glw/cryosentinel-terramind-v3 — includes `soup.ckpt` (production), five SWA snapshots, single-best checkpoint, and per-chip diagnostic Parquet files.
- **Training & evaluation dataset** — Open Data Commons Attribution License v1.0 (ODC-By 1.0) — https://huggingface.co/datasets/abzal-glw/cryosentinel-glof-v3 — Hugging Face / DataCite DOI **10.57967/hf/8823**. 42,237 chips, ≈ 30.4 GiB.
- **Per-band normalisation statistics**, the spatial-block-split hash specification, the eleven-fix configuration delta, and the MNDWI audit script are all in the public GitHub repository.

Single-command reproduction of the headline results:

```
bash scripts/reproduce_benchmarks.sh
```

This invokes a Modal H100 job that downloads the validation and test chips from `abzal-glw/cryosentinel-glof-v3`, runs the model with TTA, and writes per-chip diagnostics — runtime ≈ 25 min, cost ≈ $3. Local-GPU reproduction (24 GiB minimum) is documented in `docs/REPRODUCING.md`.

Upstream data sources require their own attribution: ESA Copernicus open-access terms for Sentinel-1, Sentinel-2, and Copernicus DEM 30 m; PANGAEA CC-BY 4.0 for the Kumar & Vijay (2026) glacial-lake inventory [DOI 10.1594/PANGAEA.983845].

10. Conclusion

We have presented CryoSentinel, a multimodal foundation-model semantic segmenter for glacial lakes in High Mountain Asia. By combining Sentinel-1 SAR, Sentinel-2 optical, and Copernicus DEM imagery through a TerraMind-1.0 Large encoder with a UperNet decoder and training under a 17-km-buffered spatial-block-split protocol, we report a validation IoU of 0.9557 — a +4.27 percentage point improvement over the most directly comparable prior single-modality result. An independent MNDWI-based label-noise audit identifies seven Kumar-polygon mislabels in the test split and raises the label-corrected test IoU from 0.8918 to 0.9082, while per-region out-of-domain transfer to Zhetysu Alatau reaches 0.9312.

The contribution is intended as a research-stage, public-good artefact: every input, output, and configuration choice is released under permissive licences with persistent DOIs, the eleven configuration corrections that account for the v1 → v2 improvement are documented in detail, and the label-noise audit methodology is released as a reusable cross-check for downstream glacial-lake inventory work.

The next milestones are (v1.1, June 2026) multi-seed variance estimation and MC-dropout uncertainty quantification, (v1.2, later 2026) temporal modelling over multi-year chip stacks, and an out-of-HMA evaluation phase extending the protocol to the Andes, the European Alps, and the Caucasus.

Funding

This work received no external funding. Cloud compute was provided by Modal Labs research credits.

Author contributions

A. Abdrash designed the study, implemented the system, ran the training and evaluation, and wrote the manuscript.

Conflict of interest

The author declares no conflicts of interest.

Acknowledgments

We thank IBM Research and the ESA Φ-lab for releasing TerraMind 1.0 under a permissive licence; Kumar and Vijay for publishing the High Mountain Asia glacial-lake inventory on PANGAEA; Adhikari and Regmi for the Sentinel-1-only baseline against which this work is compared; Modal Labs for cloud compute; and Hugging Face for hosting the model weights and dataset. We acknowledge the institutional GLOF early-warning work of Kazselezashchita (Almaty oblast, Kazakhstan) and the UNESCO GLOFCA programme — the context this research is positioned to complement, not replace.

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Figures. Reference list of figures to render in the final PDF from `_publish_drafts/cryosentinel-public/docs/figures/`:

- *Figure 1.* Sentinel-2 L2A true-colour panorama of the Ile Alatau range with Almaty (top-left) and Lake Issyk-Kul (bottom-right). File: `landscape_ile_alatau_s2.png`. Place after §1 introduction.
- *Figure 2.* Four-panel label-noise audit at 42.99° N / 76.71° E, 2023 (Sentinel-2 RGB | MNDWI | Kumar GT mask | CryoSentinel prediction). File: `hero_label_noise_audit.png`. Place inside §6.3.
- *Figure 3.* Four-panel for the 2021 acquisition of the same chip. File: `label_noise_2021_42p9998_76p7119.png`. Supplementary.
- *Figure 4.* Four-panel for the 2022 acquisition of the same chip. File: `label_noise_2022_42p9897_76p7119.png`. Supplementary.
- *Figure 5.* Non-glacial water suppression on the Tekeli reservoir (Zhetysu Alatau) between pretrain Stage 4a and finetune Stage 4b. File: `non_glacial_water_suppression_tekeli.png`. Place inside §8.4.
- *Figure 6.* Zero-shot validation cluster (Bao reservoir region). File: `zero_shot_validation_bao_cluster.png`. Place inside §5 or §7.

Tables 1–6 are inline within the relevant sections above.