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LETTER

Post-processing Subglacial Physics Model with Per-site JEPA Specialist Models Enable Natural-language Glaciological Intelligence

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Abstract

Glaciers slide over their beds, and how fast they slide depends on the pressure of meltwater trapped beneath them. This subglacial environment is nearly impossible to observe directly and is one of the largest uncertainties in how fast glaciers lose ice and how much water they deliver to communities downstream. Ice-sheet models represent it with empirical rules that are hard to test, and although machine learning and queryable artificial-intelligence systems are now reshaping much of earth science, no comparable interpretable-learning analysis or embedding-model system yet exists for subglacial processes. We address this gap in two ways. Treating coupled physics-based subglacial hydrology and ice velocity simulations of four contrasting glaciers (Himalaya, Antarctica, southeast Greenland, and northwest Greenland) as controls, we use interpretable machine learning, from linear models to recurrent networks, to understand what controls sliding. We find that bed water pressure relates to ice surface flow speed once the sliding component is isolated from the deformation component($r = -0.50$). The predictive memory of the system mostly lives in the present state of the bed, regardless of meltwater history, with state-aware models reaching $R^2 = 0.84$ against 0.24 without it. Across the four test glaciers two consistent regimes emerge - one dominated by water pressure and the other by bed shape, while instantaneous meltwater input is essentially never the direct control, indicating where common sliding rules may not apply. Leveraging these findings, we build a natural-language glaciological intelligence system for subglacial processes: a fleet of self-supervised graph foundation models, one joint-embedding predictive architecture (JEPA) per glacier, that learn rich, non-degenerate representations. These are queried through an agentic large-language-model (Claude Sonnet/Opus) router that retrieves from the appropriate specialist and improves answer quality compared to baseline, with the value of added context scaling with the consuming model’s reasoning ability.

1 Introduction

Glaciers and ice sheets move through a combination of deformation and by sliding over their beds, and the rate of sliding is set by the pressurized water system at the ice-bed interface [1, 2]. Classical and modern sliding laws relate basal motion to the effective pressure, which is defined as the difference between the ice overburden and the subglacial water pressure, and to the basal shear stress, so that a glacier with lower effective pressure tends to slide faster [3, 4, 5, 6, 7]. The subglacial drainage system that sets this pressure evolves over hours to seasons as its geometry adapts, with features such as channels and distributed cavities that open due to melt and sliding, and close as a result of ice creep [2, 8, 9]. This dynamic system is represented in coupled models such as the Subglacial Hydrology and Kinetic, Transient Interactions model (SHAKTI) within the Ice-sheet and Sea-level System Model (ISSM) [10, 11]. Coupled simulations are the principal quantitative window we have onto a system that impacts ice loss and downstream water availability. That window is needed because the bed itself is almost impossible to observe through field measurements or remote sensing techniques. The quantities a sliding law depends on (effective

pressure, subglacial water pressure, and basal sliding speed) can be sampled directly only through sparse boreholes [12, 13, 14], while the surface velocities that are routinely mapped from satellites mix basal sliding with internal ice deformation. Inferring basal conditions from surface motion is therefore an underdetermined inverse problem [15], and even the first-order question of whether effective pressure or bed strength dominates fast flow remains contested [16]. As a result, empirical sliding laws are difficult to constrain from observation and may not hold as the climate and the drainage system change [9, 17], yet the physics-based simulations that could fill the gap are computationally expensive to run across many glaciers and scenarios [11].

Machine learning is being widely used to address parts of this problem in glaciology and the wider Earth sciences. Deep networks now emulate ice flow and glacier evolution orders of magnitude faster than the solvers they replace [18, 19], and surrogate and physics-informed models have been used to infer basal mechanics from surface observations [15, 20]. More broadly, data-driven methods are increasingly leveraged for process understanding [21] by interpretability tools such as permutation importance and additive feature attribution [22, 23], aligning with a growing practice of physically interpretable modeling in the geosciences [24, 25]. For physical systems with memory, recurrent architectures [26] have been widely used: in catchment hydrology, long short-term memory networks reproduce storage-driven, lagged responses that static models may miss [27, 28, 29].

In parallel, representation learning is transforming environmental data are stored and queried. Self-supervised methods learn general-purpose embeddings without labels by predicting masked content in a latent space while regularizing against collapse [30, 31, 32, 33], and geospatial foundation models now compress satellite and atmospheric observations into dense, reusable vectors [34, 35, 36]. Graph neural networks extend these ideas to the irregular meshes on which glacier models are solved [37, 38, 39]. At the same time, large language models equipped with retrieval and tools have made structured scientific data accessible through natural language [40, 41, 42]. Recent work has combined these threads for land-surface remote sensing, interpreting foundation-model embeddings physically and routing natural-language queries to specialized encoders through an agentic interface [43, 44, 45].

Several gaps remain specific to the subglacial problem. Interpretable machine learning has rarely been applied to subglacial hydrology and sliding to ask which physical controls actually dominate. Because the hydrology, geometry, and ice dynamics are tightly coupled, aggregate correlation analyses are vulnerable to confounding, which motivates model classes whose attributions can be inspected directly. Whether the modeled sliding response carries temporal memory, and if so whether that memory resides in the recent forcing or in the present state of the bed, has not been examined systematically with sequence models on simulated subglacial systems. Whether controls learned at one glacier transfer to geometrically distinct glaciers is likewise largely unanswered. Finally, the self-supervised representations and agentic, queryable interfaces now common for satellite imagery [35, 43] have not been extended to the output of subglacial models, leaving no accessible way for non-specialists to interrogate simulated glacier behavior.

We bring these threads together for subglacial processes. We treat coupled SHAKTI-ISSM simulations of four contrasting glaciers (and region of glaciers, in one case) as controls in which the governing physics is prescribed and every relevant field is available, use interpretable machine learning to identify the controls on sliding and to test whether they transfer across glaciers, and operationalize the learned structure as a fleet of self-supervised graph encoders queried through an agentic large-language-model router, transposing a paradigm developed for land-surface and hydrology [45, 43, 44] to glacier meshes.

We ask five research questions:

1. Can interpretable models reproduce simulated basal sliding within and across glaciers?
2. Can interpretable machine learning recover an effective-pressure control on sliding?
3. Where does the predictive memory of the sliding response reside?
4. Do the dominant controls form consistent cross-glacier regimes, hydraulic versus geometric, that indicate where sliding-law parameterizations break down?
5. Can a self-supervised per-glacier fleet learn explainable embeddings that an agentic router queries to improve natural-language answers?

We address the first four questions with interpretable supervised models and cross-site benchmarking, and the fifth with the self-supervised fleet and its routed evaluation.

2 Methods

2.1 Model description

SHAKTI is a two-dimensional subglacial hydrology model that simulates water flow driven by hydraulic gradients while solving the coupled physical equations conserving water and ice mass, momentum, energy, and evolving subglacial drainage geometry [10, 46], representing the full continuum from distributed to channelized drainage. Model output includes spatiotemporally variable fields of hydraulic head, effective pressure, basal water flux, basal melt rate, and subglacial gap height. Other quantities such as hydraulic transmissivity, water pressure, and Reynolds number can also readily be calculated from these variables.

ISSM is an open-source, thermo-mechanical finite-element model that simulates glacier and ice sheet flow using higher-order physics [11]. SHAKTI is built into ISSM as a hydrology module. Implemented within ISSM, SHAKTI has been applied to Greenland, Himalayan, and Antarctic glaciers in both stand-alone and coupled simulations [46, 47, 48, 49, 50]. Coupling occurs through the basal sliding law, which links effective pressure calculated by SHAKTI with glacier sliding velocity calculated by the stress balance in ISSM.

2.2 Study sites and coupled simulations

We analyze output from coupled SHAKTI-ISSM simulations. We consider simulations of four glacier domains chosen to span contrasting climates, geometries, and basal regimes (Figure 1): Drang Drung, a mountain glacier in Ladakh, Himalaya; Helheim Glacier, a fast-moving outlet glacier in southeast Greenland; a large section of the northwest Greenland Ice Sheet; and Thwaites Glacier in the Amundsen Sea sector of Antarctica. This collection of model experiments includes a variety of spatiotemporal forcings in different settings. Following is a summary of the specific simulations included in our analysis.

Drang Drung Glacier [51] is a Himalayan glacier that shows observational evidence of a seasonal velocity signal hypothesized to be driven by variations in subglacial hydrology, with SHAKTI-ISSM supporting that theory [49, 52]. Drang Drung moves less than 20 m per year near its terminus, with a maximum velocity on the order of 100 m per year in its thickest upstream portion. The ice is less than 500 m thick throughout the glacier [53]. We consider a spin-up winter simulation presented in [49], along with several transient simulations forced by hourly water inputs to the bed down-scaled from the ERA5 climate model (CITE) output of snow melt, ice melt, and liquid precipitation. In these transient SHAKTI-ISSM simulations, the quantity of water that reaches the bed is scaled linearly as a function of elevation with the full amount of local water delivered to the bed at the terminus, and zero water reaching the bed at the equilibrium line altitude, and is applied in a distributed manner over the bed, assuming instantaneous delivery to the subglacial system. The elevation dependence is designed to account broadly for percolation, storage, and refreezing at higher elevations. The assumption of instantaneous delivery to the bed is not particularly realistic; in reality, meltwater and precipitation would get routed by supraglacial streams and percolate through the ice, imposing a delay in the time it takes for water to reach the bed. However, the instantaneous meltwater delivery and instantaneous response of the subglacial system are useful experimental conditions for probing model physics and response to hourly variations in forcing. Our Drang Drung simulations use the MOno-layer Higher Order (MOLHO) ice flow approximation [54] and a regularized Coulomb friction parameterization commonly referred to as the Schoof sliding law [5].

Helheim Glacier is a large, fast-moving tidewater outlet glacier in southeast Greenland that has been the focus of previous SHAKTI modeling efforts [46, 47]. In contrast to Drang Drung, which moves with a maximum velocity on the order of 100 m per year in its thickest portion, Helheim moves several km per year in its main trunk, which terminates in a deep fjord. The ice is more than 1 km thick [55]. In this study, we consider three different coupled SHAKTI-ISSM simulations from [47] that apply seasonal meltwater forcing: one in which distributed meltwater is applied below 2000 m ice surface elevation following runoff based on MERRA-2 climate reanalysis (CITE); a second in which the same low-elevation meltwater is applied, along with point inputs of water at higher elevations to represent drainage through crevasses of water stored in the upstream firn aquifer; and a third simulation that includes both distributed and point inputs, with an increase in magnitude to represent enhanced surface melt under future warming conditions. The simulations use the Shallow Shelf Approximation (SSA) for ice flow [56], a reasonable approximation for fast-moving glaciers, and the Budd sliding law [?]. These experiments are described in detail by [47].

At Helheim Glacier and at Thwaites Glacier in Antarctica, we also consider a set of unconventional simulations from [48] that model the response to extraction of water from the

Table 1. Data assembled at each mesh vertex. Modeled fields come from coupled SHAKTI-ISSM simulations; auxiliary fields are sampled from Google Earth Engine. After removing basal shear stress and constant columns, approximately 83 features remain per vertex, of which AlphaEarth contributes 64.

Group	Variable	Source	Role
Subglacial hydrology	effective pressure N	SHAKTI-ISSM	predictor (bed state)
	hydraulic head	SHAKTI-ISSM	predictor (bed state)
	water flux	SHAKTI-ISSM	predictor
	gap height	SHAKTI-ISSM	predictor
Ice dynamics	basal shear stress τ_b	SHAKTI-ISSM	excluded from features
	basal sliding speed u_b	SHAKTI-ISSM	prediction target
	total ice velocity	SHAKTI-ISSM	prediction / analysis target
Geometry	surface elevation z_s	model / DEM	predictor
	bed elevation z_b	model / DEM	predictor
	ice thickness H	model	predictor / stratifier
Forcing	meltwater input	model forcing	predictor
Satellite embedding	AlphaEarth (64-d)	Google Earth Engine	predictor (fleet)
Climate	ERA5-Land reanalysis	Google Earth Engine	predictor
Land surface	MODIS temperature, snow cover	Google Earth Engine	predictor
Topography	elevation and slope (DEM)	Google Earth Engine	predictor

subglacial system at 11 arbitrary sites on each glacier, simulated as negative point sources of meltwater. These experiments are useful for exploring the response of the glaciers to perturbations in the subglacial system and are motivated by a potential intervention scheme of pumping water from beneath glaciers in order to slow their sliding. Thwaites is a large glacier that includes a floating ice shelf, has the potential to unleash a large amount of ice from Antarctica into the ocean if it retreats substantially, is thicker and flows more slowly than Helheim. These simulations use SSA and Budd sliding.

The fourth simulation applies SHAKTI-ISSM to a large region in the northwest of the Greenland Ice Sheet, which includes many outlet glaciers with variable geometry. Seasonal meltwater is prescribed, based on runoff estimates from average climatology over 2003-2022 in the MERRA-2 climate reanalysis model [57]. Water inputs to SHAKTI are distributed spatially and assume instantaneous local delivery to the bed. This simulation uses SSA to approximate ice flow and the Budd friction parameterization.

All simulations are run using unstructured triangular finite element meshes with variable resolution. The various model configurations included in this suite of SHAKTI-ISSM simulations differ in their prescribed sliding relationships, spanning regularized-Coulomb [5] and Budd-type [?] laws, so that the learning task is not tied to a single basal parameterization. The Drang Drung simulations use MOLHO [54] for the stress balance, which explicitly separates ice surface velocity from basal sliding velocity, while the others use SSA [56] in which the ice velocity is assumed to be uniform through the ice column (justifiable for fast-moving glaciers). Each simulation spans at least one year, and we focus our temporal analyses on the melt season, when the subglacial system is most active; the held-out evaluation protocol for each analysis is described below.

At every mesh vertex we assemble a feature vector that combines modeled subglacial and ice-dynamic fields with co-located geometry, climate, and satellite information (Table 1). Auxiliary fields are sampled at the vertices from Google Earth Engine. Basal shear stress and constant columns are removed, leaving approximately 83 features per vertex, of which the AlphaEarth embedding contributes 64. For the graph models below, each glacier is represented as a mesh graph obtained by Delaunay triangulation of its vertices, with edges carrying relative position and distance. The full workflow is summarized in Figure 2.

2.3 Interpretable supervised modeling

We use a ladder of supervised models to address research questions one through four. For the focal glacier, Drang Drung, which has the most extensive multi-year forcing, we compare a linear baseline, a random forest [22], and a long short-term memory network [26] that predict basal sliding; the linear and random-forest models receive per-vertex features with multi-day forcing lags, while the recurrent model receives multi-day sequences of forcing together with the bed state. These models are trained on early simulation years and evaluated on a shared held-out set of later melt-season years, so that skill is measured on unseen conditions and is directly comparable across models (research question one, within glaciers). To assess reproduction across glaciers and to compare controls between them, we additionally train one random forest per glacier on a compact, physically interpretable feature subset, namely effective pressure, hydraulic head, ice thickness, surface and bed elevation, and meltwater input, each evaluated on a held-out split of its own

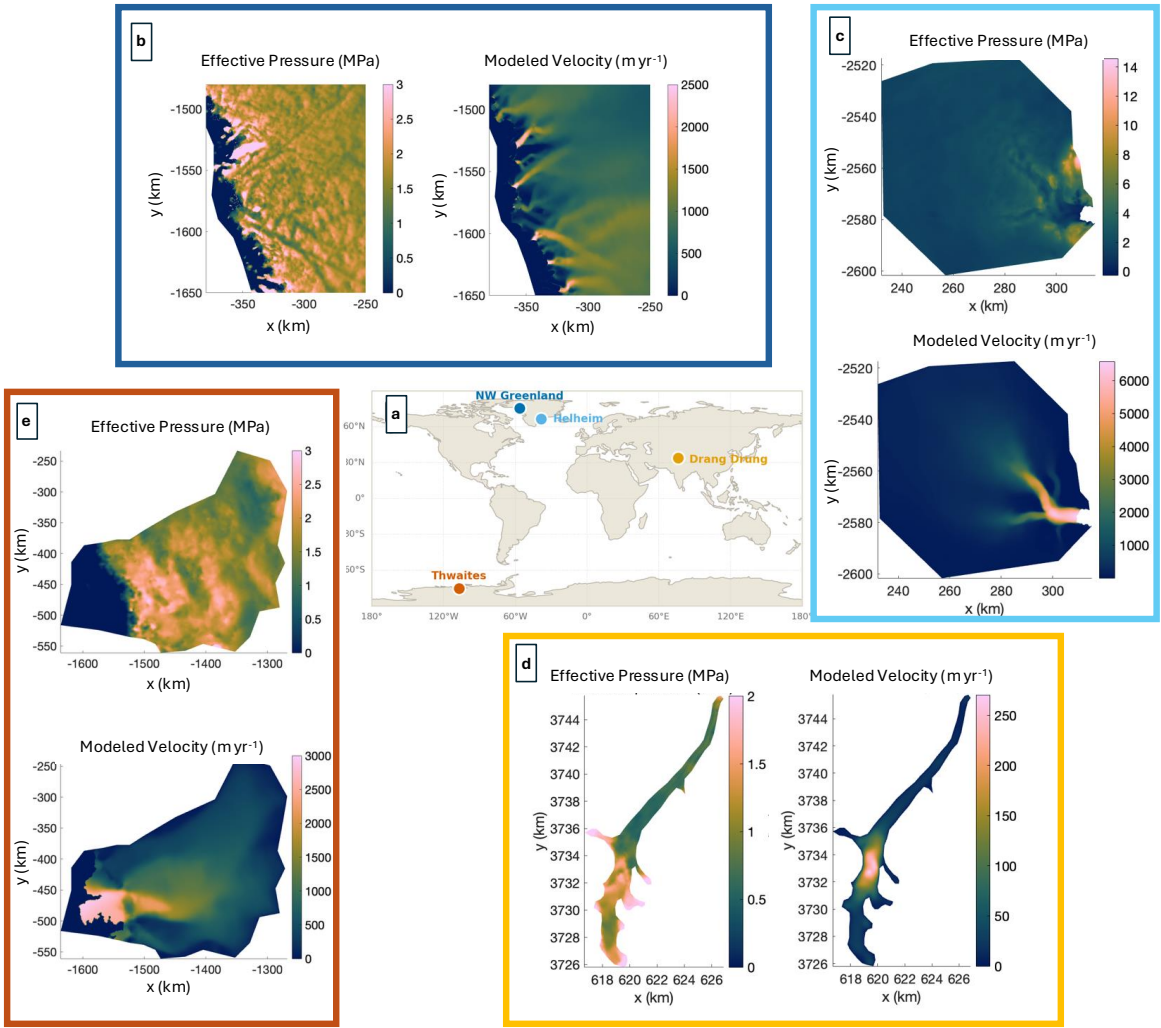
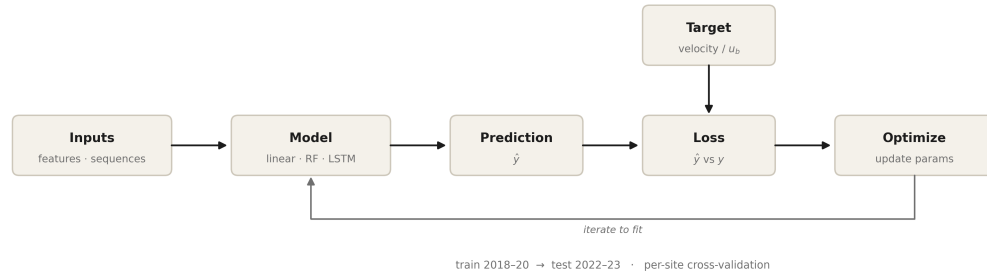


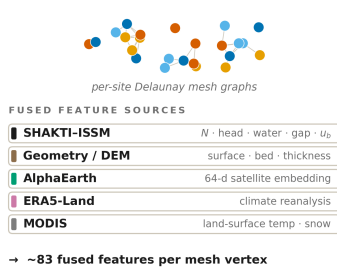
Figure 1. Study sites. (a) Global locations of the four glacier domains. Modeled winter effective pressure and ice surface velocity (b) northwest Greenland, (c) Helheim Glacier in southeast Greenland, (d) Drang Drung Glacier in Ladakh, India, and (e) Thwaites Glacier in Antarctica.

Supervised modeling

predict ice velocity / basal sliding u_b from the fused mesh features



1 Data



2 GNN-JEPA pretraining

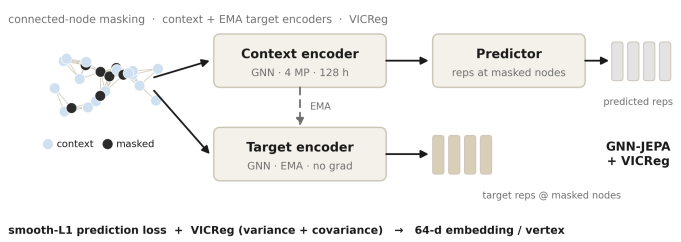


Figure 2. Modeling overview. Top: the supervised training loop, in which fused per-vertex features and multi-day sequences drive a model ladder (linear, random forest, recurrent network) to predict basal sliding, with models trained on early years and tested on later years. Bottom: (1) the data sources fused at each mesh vertex and (2) the self-supervised graph joint-embedding-predictive architecture, comprising connected-node masking, a context encoder, an exponential-moving-average target encoder, a predictor, and a variance-covariance objective that yields a 64-dimensional embedding at every vertex.

simulation; at the fast outlet glaciers ice velocity is dominated by basal sliding, so reproducing velocity there is effectively reproducing sliding (research question one, across glaciers).

Three analyses build on these models. First, to test whether an aggregate view of total velocity can obscure the effective-pressure control (research question two), we examine the relationship between effective pressure and motion at Drang Drung both in pooled form and after stratifying by ice thickness and isolating the basal sliding component. Second, to locate the predictive memory of the system (research question three), we compare the Drang Drung models supplied with different information, namely instantaneous forcing, forcing extended with several days of history, the present bed state alone, and forcing combined with the bed state, contrasting the random forest with the recurrent network on the identical evaluation set. Third, to compare controls across glaciers (research question four), we quantify each feature's contribution to the per-glacier random forests with impurity-based and permutation importance [22, 23], and we summarize each glacier in a two-axis control plane defined by its reliance on hydraulic variables (effective pressure and hydraulic head) versus geometric variables (bed elevation and ice thickness). The supervised workflow is shown in the upper panel of Figure 2.

2.4 Self-supervised graph foundation-model fleet

To turn each glacier into a reusable representation (research question five), we pretrain one self-supervised graph encoder per site using a joint-embedding predictive architecture (JEPA) [30, 31]. The encoder embeds vertex features through a linear projection and four rounds of message passing over the mesh graph, in which each vertex aggregates information from its neighbors weighted by relative position, and outputs a 64-dimensional vector per vertex [37, 38, 39]. Following the joint-embedding predictive recipe, we mask connected patches of the graph grown from random seed vertices, encode the graph with a context encoder, and train a predictor to reproduce, in latent space, the embeddings that a separate target encoder assigns to the masked vertices. The target encoder is an exponential moving average of the context encoder and receives no gradients [33]. The training objective combines a smooth-L1 prediction loss with a variance-covariance regularization term that prevents representational collapse [32], and each encoder is trained with the AdamW optimizer under a cosine learning-rate schedule. As a diagnostic of representation quality that requires no downstream label, we compute the effective dimensionality of the learned embeddings, which indicates how many independent directions the representation actually uses out of the available sixty-four. The architecture is shown in the lower panel of Figure 2.

2.5 Agentic routing and evaluation

Finally, we leverage the fleet through an agentic retrieval interface, which we refer to as Glacier Intelligence (Figure 3). For each glacier, we build two nearest-neighbor indices over its vertices, one over the learned 64-dimensional embeddings and one over the AlphaEarth embeddings, using inner-product search on normalized vectors [42], and we attach a short capability card that summarizes each site. A large language model serves as the system: given a natural-language question, it reads the capability cards, selects which glaciers are relevant, and issues retrieval calls, after which a synthesis step composes an answer from the returned, provenance-tagged vertices [40, 41]. We evaluate three configurations of increasing access: retrieval from the AlphaEarth generalist only, routed retrieval from the selected glacier specialists, and a dual configuration that combines the specialists with the generalist. We run the system with two language models of differing capability (Claude Sonnet 4.6 and Claude Opus 4.7) over a stratified set of questions, and we score each answer with a separate model acting as judge along four dimensions, physical correctness, use of retrieved evidence, awareness of basal regime, and clarity, while separately measuring routing accuracy against the intended glaciers with the Jaccard index. The system model and the judge model are kept distinct so that no model evaluates its own output.

3 Results

3.1 Interpretable models reproduce simulated sliding

We first ask whether interpretable models can reproduce the simulated basal sliding (Figure 4). At the focal glacier, Drang Drung, a linear model captures little of the sliding ($R^2 = 0.23$), and an LSTM given only meltwater forcing does little better ($R^2 = 0.24$). A random forest that also sees the state of the bed reaches $R^2 = 0.62$, and an LSTM that tracks the bed through time reaches $R^2 = 0.84$. The same approach works at every glacier: per-glacier random forests reproduce ice velocity with R^2 of 0.67 at Drang Drung, 0.96 at Helheim, 0.93 at Thwaites, and 0.72 at the northwest Greenland margin, with skill highest where flow is fastest and most clearly dominated by

Glacier Intelligence

natural-language access to the mini-JEPA fleet via routed retrieval

1 Query

2 Route

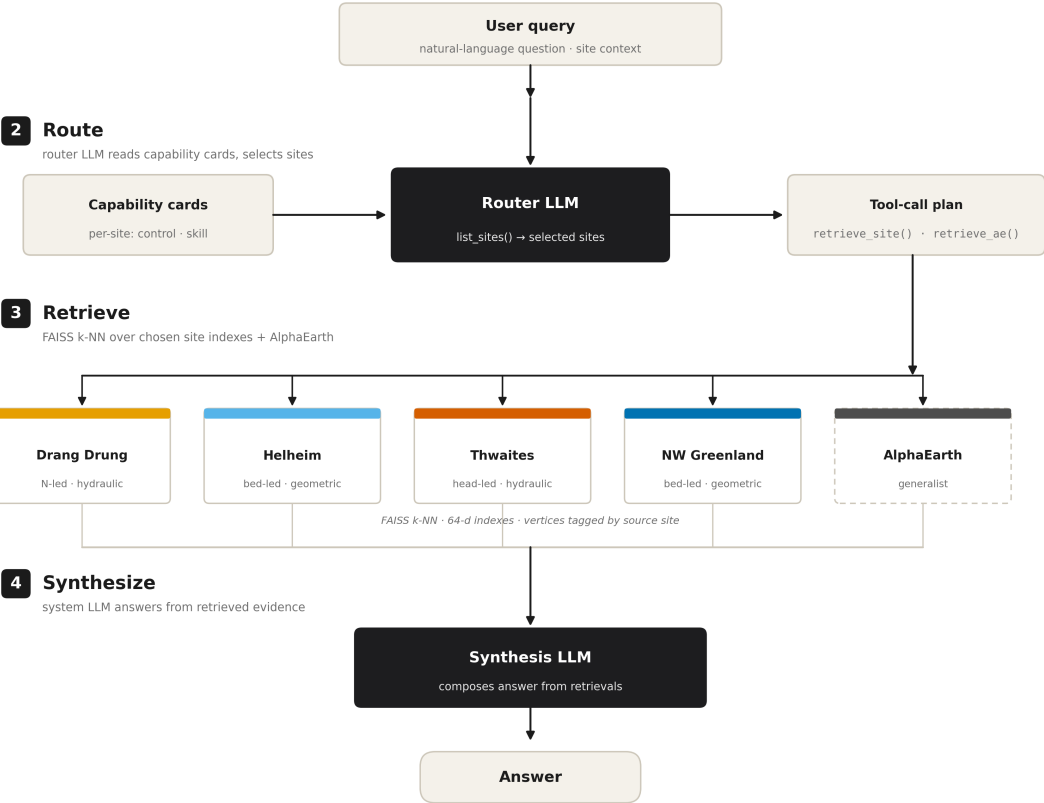
router LLM reads capability cards, selects sites

3 Retrieve

FAISS k-NN over chosen site indexes + AlphaEarth

4 Synthesize

system LLM answers from retrieved evidence



system model: Claude Sonnet 4.6 (n=160) · Claude Opus 4.7 (n=40) — cross-model LLM-as-judge C2 AE-only · C4 multi-select · C5 dual-RAG

Figure 3. The Glacier Intelligence agentic routing pipeline. A natural-language query is routed by a language model that reads per-glacier capability cards and emits retrieval calls; nearest-neighbor retrieval over the per-glacier learned embeddings and an AlphaEarth generalist returns provenance-tagged evidence that a synthesis step composes into an answer.

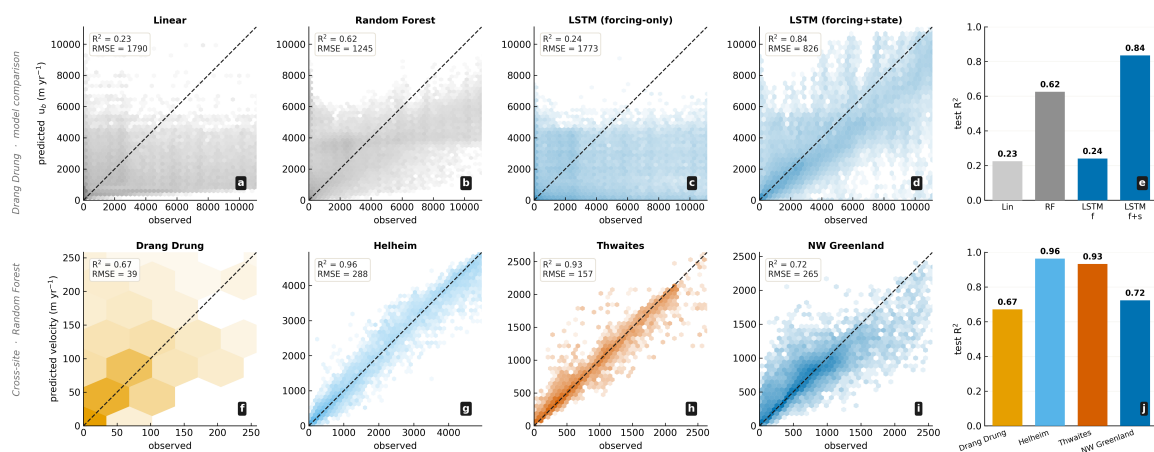


Figure 4. Interpretable models reproduce simulated sliding. Top: predicted versus simulated basal sliding at Drang Drung for a linear model, a random forest, an LSTM given only forcing, and an LSTM given forcing and bed state, with the coefficient of determination summarized in the right-hand bar. Bottom: predicted versus simulated ice velocity for a per-glacier random forest at each of the four glaciers, with the corresponding skill in the right-hand bar.

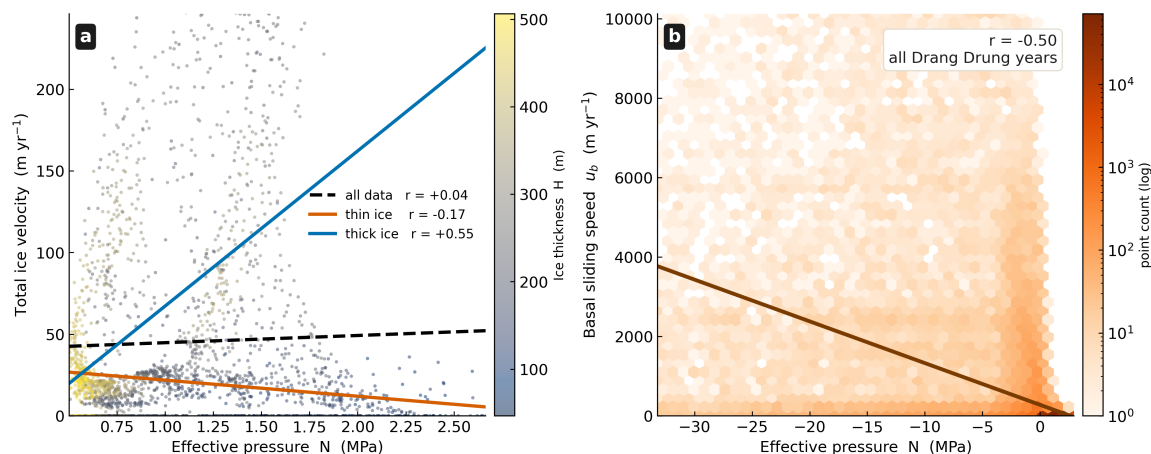


Figure 5. A hidden effective-pressure control. Left: effective pressure against total ice velocity at Drang Drung, shown pooled and split by ice thickness; the pooled correlation is near zero while thin and thick ice show opposite tendencies. Right: effective pressure against the isolated basal sliding component, where the expected negative relationship is clear.

sliding. The simulated sliding is learnable, but only by models given information on the bed's condition. This highlights the difficulty in predicting glacier sliding from observable variables and points to the need for more efficient representation of subglacial hydrology in large-scale models.

3.2 A hidden effective-pressure control on sliding

Physically, a bed held at higher effective pressure (that is, lower water pressure) with all else equal should slide more slowly, so effective pressure and motion should be negatively related. Yet when we correlate effective pressure against total ice velocity across Drang Drung, the relationship nearly vanishes ($r = +0.04$) and even tips slightly the wrong way (Figure 5). This is a textbook confound. Splitting the same data by ice thickness reveals opposite tendencies in thin and thick ice ($r = -0.17$ and $r = +0.55$) that cancel when pooled, and total velocity additionally mixes sliding with internal deformation, which dilutes the signal. When we isolate the modeled basal sliding component, the expected control reappears clearly ($r = -0.50$): higher effective pressure does slow the sliding speed. The lesson is that an aggregate, correlation-level look at velocity can make a real and important control appear irrelevant, and the physics is recovered only once the right quantity is isolated. When using modeled velocity, separating basal sliding from deformation is possible if the ice flow model was run either in 3D (using Full-Stokes or Higher Order) or using a 2D depth-integrated Higher Order model, as is the case for the Drang Drung model. For fast-moving outlet glaciers in Greenland and Antarctica where most of the surface velocity can be reasonably attributed to sliding, 2D SSA may be more acceptable than in slower-moving mountain glaciers.

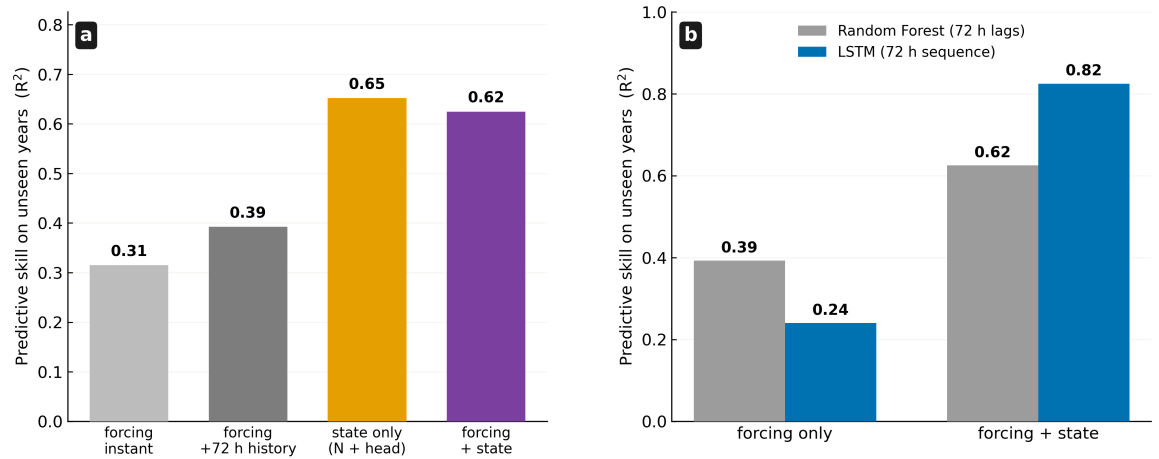


Figure 6. Predictive memory resides in the bed state. (a) Skill of a random forest given instantaneous forcing, forcing plus several days of history, the present bed state alone, and forcing combined with the bed state. (b) Skill of the random forest versus the LSTM, with and without the bed state, showing the extra skill the LSTM gains by following the bed through time.

3.3 Predictive memory resides in the state of the bed

Does the sliding response remember its past forcing, and if so, where is that memory stored (Figure 6)? Meltwater forcing on its own is a weak predictor, whether we use the instantaneous value ($R^2 = 0.31$) or add several days of history ($R^2 = 0.39$). The present state of the bed, summarized by effective pressure and hydraulic head, predicts sliding much better ($R^2 = 0.65$), and adding the forcing history on top of the state adds nothing beyond the state alone ($R^2 = 0.62$ versus 0.65). Giving an LSTM both the forcing and the evolving state raises skill further to $R^2 = 0.84$, because it can follow how the state changes over time, but the central point stands: the memory that matters for sliding lives in the bed's present condition, not in the recent record of melt. Again, this result highlights the difficulty in predicting glacier response solely based on melt.

3.4 Two cross-glacier control regimes

Comparing which variables the per-glacier models rely on reveals a clean split (Figure 7). At Drang Drung the water system dominates, with effective pressure and head together accounting for most of the importance, and Thwaites is similarly led by hydraulic head. This finding at Thwaites is particularly noteworthy, based on the water extraction simulations studied here. Antarctica does not currently experience much (if any) seasonal surface meltwater that drains to the bed, but that may change as the climate warms. It could shift to a regime more similar to Greenland, with strong seasonal dynamic cycles. Our results show that the behavior of Thwaites is sensitive to variations in subglacial water pressure. At Helheim and the northwest Greenland margin, by contrast, the bed's shape dominates, with bed elevation and ice thickness carrying most of the weight. Across all four glaciers the meltwater input itself carries almost no direct importance, reinforcing that what matters is the pressure state the input produces, not the timing, magnitude, or location of input. Placing each glacier on a plane of hydraulic reliance versus geometric reliance separates them into two regimes (Figure 8): hydraulically controlled beds (Drang Drung, Thwaites) and geometrically controlled beds (Helheim, northwest Greenland). The separation holds when the analysis is restricted to physical variables. This matters for parameterization: a sliding law tuned for a hydraulically controlled bed should not be expected to transfer to a geometrically controlled one, and the plane indicates where that mismatch is likely. While much research is aimed at finding a universally applicable sliding law, this finding suggests that a single universal law might not be possible or appropriate, but rather that distinct parameterizations could be used based on the dominant control.

3.5 Reusable embeddings and improved routed answers

We examine the self-supervised fleet and its routed interface. We see stable training for the per-glacier encoders, with the prediction loss falling by about an order of magnitude and no indication representational collapse. The learned embeddings use roughly 25 to 27 of their 64 available dimensions (Figure 9), indicating rich but compact representations. On the question-answering evaluation (Figure 10), routing a query to the relevant glacier specialist

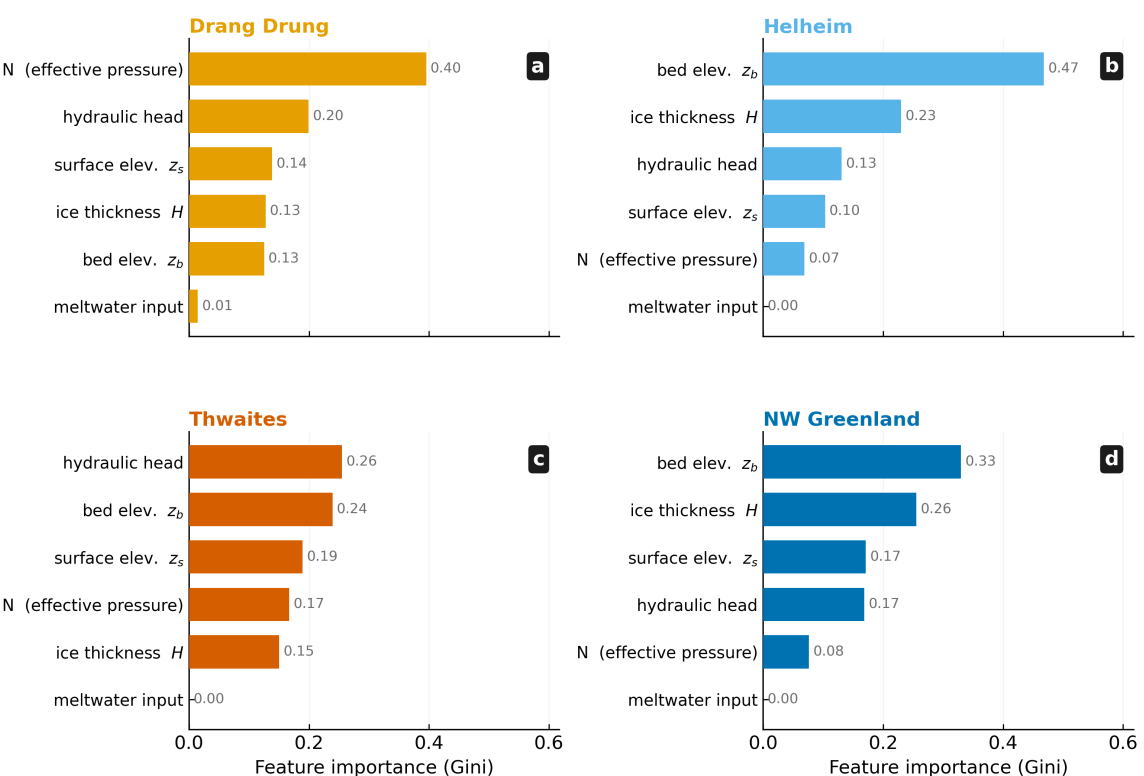


Figure 7. Dominant controls by glacier. Impurity-based feature importance for the per-glacier random forests at Drang Drung, Helheim, Thwaites, and the northwest Greenland margin. Hydraulic variables (effective pressure, hydraulic head) dominate at some glaciers and geometric variables (bed elevation, ice thickness) at others, while meltwater input is consistently unimportant.

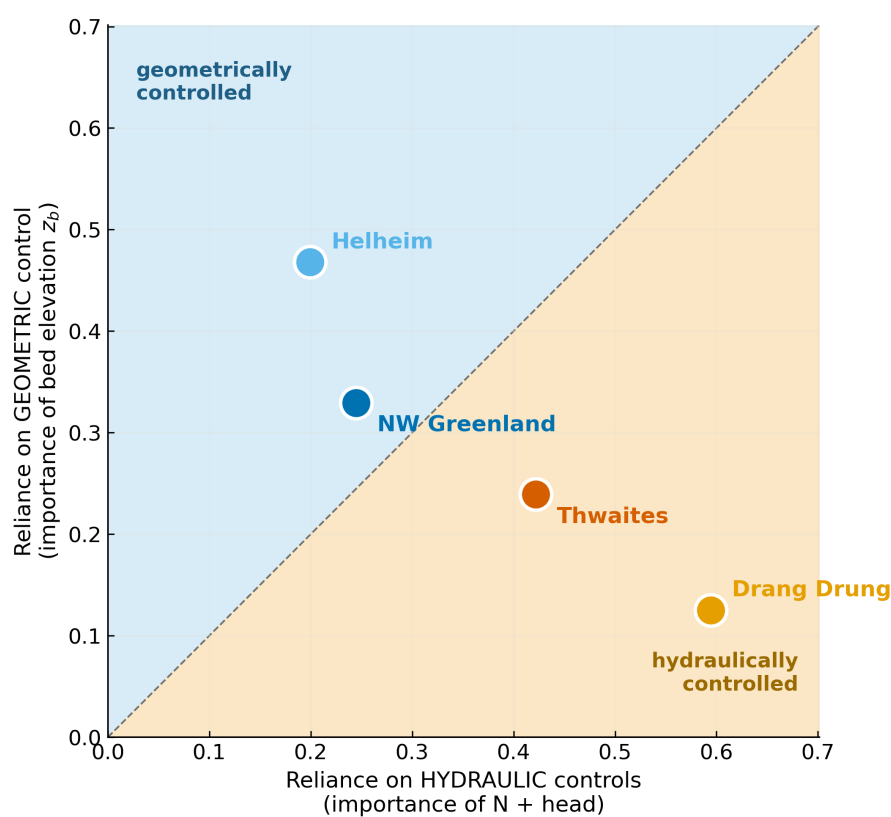


Figure 8. Two control regimes. Each glacier is placed on a plane of hydraulic reliance (importance of effective pressure and head) versus geometric reliance (importance of bed elevation and thickness). The diagonal separates hydraulically controlled beds (Drang Drung, Thwaites) from geometrically controlled beds (Helheim, northwest Greenland).

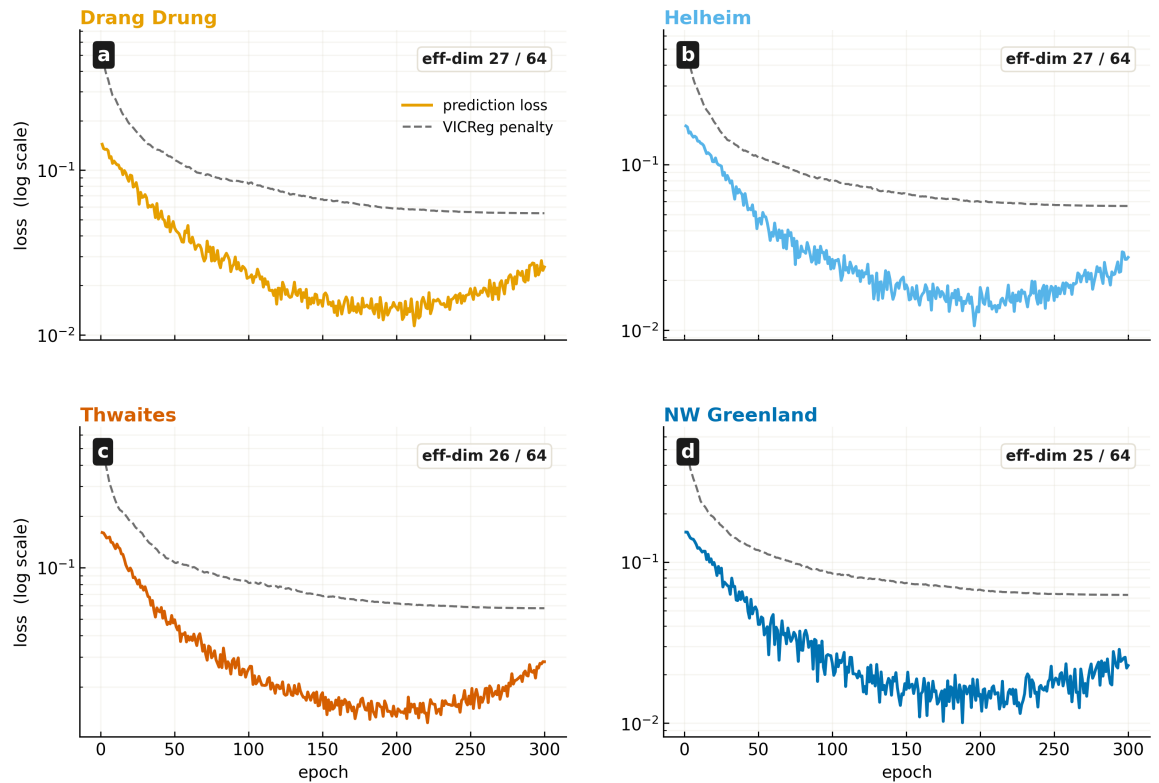


Figure 9. Self-supervised pretraining of the fleet. Training curves for the per-glacier encoders, showing the prediction loss and the variance-covariance regularization term over training on a logarithmic vertical axis; the effective dimensionality of each learned embedding is annotated. Losses fall smoothly and the embeddings show no representational collapse.

improves answer quality over a generalist-only baseline by a similar margin for both language models (about +0.21 for Claude Sonnet 4.6 and +0.20 for Claude Opus 4.7 on the judged score). Adding supplementary generalist context on top of the specialists, however, helps only the more capable model (Opus, about +0.07) and hurts the less capable one (Sonnet, about -0.24), demonstrating a pattern previously seen in land-surface embeddings [44]: extra context is useful only to a model able to reason over it. Routing itself is accurate, recovering the intended glaciers with Jaccard scores of 0.85 for Sonnet and 1.00 for Opus.

4 Conclusion

We studied basal sliding in coupled SHAKTI-ISSM simulations of four glacier domains with interpretable machine learning, and organized the learned structure into a queryable system. Interpretable models reproduce the simulated sliding once they are given the state of the bed, whereas meltwater forcing alone carries little predictive value. An effective-pressure control on sliding that appears near zero in total ice velocity becomes evident once the sliding component is isolated. The predictive memory of the response sits in the present state of the bed rather than in the recent history of melt, which the bed has already integrated into its pressure. Across the four glacier domains the dominant controls separate into hydraulic and geometric regimes, and the meltwater input is never itself a direct control. A fleet of self-supervised per-glacier encoders learns compact embeddings, and routing a question to the relevant specialist improves the answers, with added context helping only the more capable language model.

Several limitations frame these conclusions. The targets are simulator output, so the learned relationships reflect the coupled model and its prescribed sliding laws; four glaciers are enough to reveal two regimes but not to chart their full range; and the temporal analyses center on one focal glacier. The natural next steps are to extend the fleet to more glaciers and, where data allow, to test the recovered controls and regimes against borehole and surface measurements, and to grow the interface from question answering toward guided exploration of where sliding behavior diverges across settings. Together, these steps would broaden what can be learned from subglacial simulations and what can be inferred about the subglacial system from observable quantities.

Beyond the science, the longer aim is societal. How a glacier bed behaves affects how fast its ice

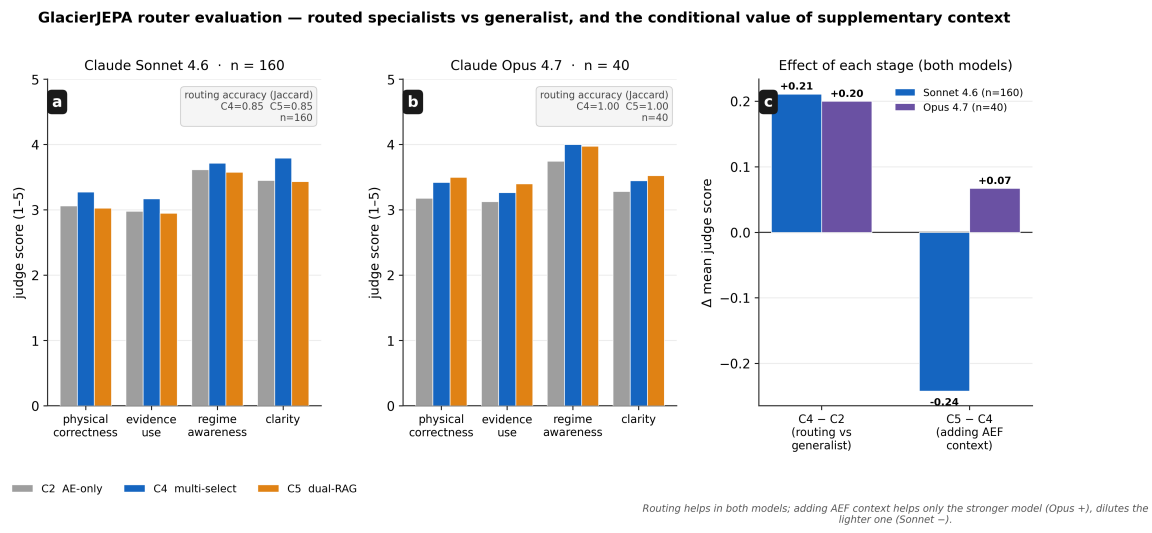


Figure 10. Routed question answering. Left: judged answer quality along four dimensions (physical correctness, use of evidence, regime awareness, clarity) for the two language models under the generalist-only, routed-specialist, and dual configurations. Right: the effect of routing (routed minus generalist-only) and of adding generalist context (dual minus routed) for each model.

is lost and how much meltwater reaches communities downstream, along with the risk of glacial flooding, yet the people and water managers who must plan around these changes rarely have access to easily scalable and useful glaciological information systems. This study is a step toward closing that gap: knowing where a model’s account of sliding can be trusted makes its projections more reliable, and making that account fast to run and simple to query brings it within reach of non-specialists, including in the data-poor regions where it matters most. The foundation it lays is a path from costly, expert-only simulations toward glacier knowledge that the people living with these changes can actually use.

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Author Contributions

Mashrekur Rahman: Conceptualization, Methodology, Software, Formal analysis, Data curation, Investigation, Visualization, Writing - original draft, Writing - review & editing. **Aleah Sommers:** Conceptualization, Methodology, Resources, Validation, Investigation, Supervision, Project administration, Funding acquisition, Writing - review & editing. Both authors contributed equally to this work and approved the final manuscript.

Data availability

All code, the trained per-glacier encoders, graph corpora, and FAISS indices, and the evaluation outputs (model responses, judge scores, and routing logs) are archived on Zenodo at <https://doi.org/10.5281/zenodo.20792803>, with development history on GitHub. The components that call the Dartmouth Chat API for routing, synthesis, and judging are omitted because that service is not publicly available; the prompts, routing logic, and query sets are included so the experiments can be reproduced against any compatible language-model endpoint. Source environmental products and their Google Earth Engine dataset identifiers are listed in Table 1, including the publicly available AlphaEarth Foundations V1 embeddings (GOOGLE/SATELLITE_EMBEDDING/V1/ANNUAL). Coupled SHAKTI-ISSM simulation outputs are available in the data repositories associated with their original publication [47, 48, 49]

References

[1] Iken A 1981 The effect of the subglacial water pressure on the sliding velocity of a glacier in an idealized numerical model *Journal of Glaciology* **27** 407–421

- [2] Flowers G E 2015 Modelling water flow under glaciers and ice sheets *Proceedings of the Royal Society A* **471** 20140907
- [3] Weertman J 1957 On the sliding of glaciers *Journal of Glaciology* **3** 33–38
- [4] Lliboutry L 1968 General theory of subglacial cavitation and sliding of temperate glaciers *Journal of Glaciology* **7** 21–58
- [5] Schoof C 2005 The effect of cavitation on glacier sliding *Proceedings of the Royal Society A* **461** 609–627
- [6] Gagliardini O, Cohen D, Råback P and Zwinger T 2007 Finite-element modeling of subglacial cavities and related friction law *Journal of Geophysical Research: Earth Surface* **112** F02027
- [7] Zoet L K and Iverson N R 2020 A slip law for glaciers on deformable beds *Science* **368** 76–78
- [8] Werder M A, Hewitt I J, Schoof C G and Flowers G E 2013 Modeling channelized and distributed subglacial drainage in two dimensions *Journal of Geophysical Research: Earth Surface* **118** 2140–2158
- [9] Schoof C 2010 Ice-sheet acceleration driven by melt supply variability *Nature* **468** 803–806
- [10] Sommers A, Rajaram H and Morlighem M 2018 SHAKTI: Subglacial hydrology and kinetic, transient interactions v1.0 *Geoscientific Model Development* **11** 2955–2974
- [11] Larour E, Seroussi H, Morlighem M and Rignot E 2012 Continental scale, high order, high spatial resolution, ice sheet modeling using the Ice Sheet System Model (ISSM) *Journal of Geophysical Research: Earth Surface* **117** F01022
- [12] Iken A and Bindschadler R A 1986 Combined measurements of subglacial water pressure and surface velocity of Findelengletscher, Switzerland: Conclusions about drainage system and sliding mechanism *Journal of Glaciology* **32** 101–119
- [13] Andrews L C, Catania G A, Hoffman M J, Gulev J D, Lüthi M P, Ryser C, Hawley R L and Neumann T A 2014 Direct observations of evolving subglacial drainage beneath the greenland ice sheet *Nature* **514** 80–83
- [14] Bartholomew I, Nienow P, Mair D, Hubbard A, King M A and Sole A 2010 Seasonal evolution of subglacial drainage and acceleration in a greenland outlet glacier *Nature Geoscience* **3** 408–411
- [15] Brinkerhoff D, Aschwanden A and Fahnestock M 2021 Constraining subglacial processes from surface velocity observations using surrogate-based Bayesian inference *Journal of Glaciology* **67** 385–403
- [16] Stearns L A and van der Veen C J 2018 Friction at the bed does not control fast glacier flow *Science* **361** 273–277
- [17] Bartholomew T C, Anderson R S and Anderson S P 2008 Response of glacier basal motion to transient water storage *Nature Geoscience* **1** 33–37
- [18] Juvet G, Cordonnier G, Kim B, Lüthi M, Vieli A and Aschwanden A 2022 Deep learning speeds up ice flow modelling by several orders of magnitude *Journal of Glaciology* **68** 651–664
- [19] Bolibar J, Rabatel A, Gouttevin I, Galiez C, Condom T and Sauquet E 2020 Deep learning applied to glacier evolution modelling *The Cryosphere* **14** 565–584
- [20] Riel B, Minchew B and Bischoff T 2021 Data-driven inference of the mechanics of slip along glacier beds using physics-informed neural networks: Case study on Rutford Ice Stream, Antarctica *Journal of Advances in Modeling Earth Systems* **13** e2021MS002621
- [21] Reichstein M, Camps-Valls G, Stevens B, Jung M, Denzler J, Carvalhais N and Prabhat 2019 Deep learning and process understanding for data-driven Earth system science *Nature* **566** 195–204
- [22] Breiman L 2001 Random forests *Machine Learning* **45** 5–32

- [23] Lundberg S M and Lee S I 2017 A unified approach to interpreting model predictions *Advances in Neural Information Processing Systems (NeurIPS)* vol 30
- [24] Toms B A, Barnes E A and Ebert-Uphoff I 2020 Physically interpretable neural networks for the geosciences: Applications to Earth system variability *Journal of Advances in Modeling Earth Systems* **12** e2019MS002002
- [25] McGovern A, Lagerquist R, Gagne D J, Jergensen G E, Elmore K L, Homeyer C R and Smith T 2019 Making the black box more transparent: Understanding the physical implications of machine learning *Bulletin of the American Meteorological Society* **100** 2175–2199
- [26] Hochreiter S and Schmidhuber J 1997 Long short-term memory *Neural Computation* **9** 1735–1780
- [27] Kratzert F, Klotz D, Brenner C, Schulz K and Herrnegger M 2018 Rainfall–runoff modelling using long short-term memory (LSTM) networks *Hydrology and Earth System Sciences* **22** 6005–6022
- [28] Shen C 2018 A transdisciplinary review of deep learning research and its relevance for water resources scientists *Water Resources Research* **54** 8558–8593
- [29] Frame J M, Kratzert F, Raney II A, Rahman M, Salas F R and Nearing G S 2021 Post-processing the national water model with long short-term memory networks for streamflow predictions and model diagnostics *JAWRA Journal of the American Water Resources Association* **57** 885–905
- [30] LeCun Y 2022 A path towards autonomous machine intelligence Tech. rep. OpenReview version 0.9.2
- [31] Assran M, Duval Q, Misra I, Bojanowski P, Vincent P, Rabbat M, LeCun Y and Ballas N 2023 Self-supervised learning from images with a joint-embedding predictive architecture *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* pp 15619–15629
- [32] Bardes A, Ponce J and LeCun Y 2022 VICReg: Variance-invariance-covariance regularization for self-supervised learning *International Conference on Learning Representations (ICLR)*
- [33] Grill J B, Strub F, Altché F, Tallec C, Richemond P H *et al* 2020 Bootstrap your own latent: A new approach to self-supervised learning *Advances in Neural Information Processing Systems (NeurIPS)* vol 33 pp 21271–21284
- [34] Jakubik J, Roy S, Phillips C E, Fraccaro P, Godwin D, Zadrozny B *et al* 2023 Foundation models for generalist geospatial artificial intelligence *arXiv preprint arXiv:2310.18660*
- [35] Brown C F *et al* 2025 AlphaEarth Foundations: An embedding field model for accurate and efficient global mapping from sparse label data *arXiv preprint arXiv:2507.22291*
- [36] Bodnar C, Bruinsma W P, Lucic A *et al* 2025 A foundation model for the Earth system *Nature* **641** 1180–1187
- [37] Kipf T N and Welling M 2017 Semi-supervised classification with graph convolutional networks *International Conference on Learning Representations (ICLR)*
- [38] Battaglia P W, Hamrick J B, Bapst V *et al* 2018 Relational inductive biases, deep learning, and graph networks *arXiv preprint arXiv:1806.01261*
- [39] Pfaff T, Fortunato M, Sanchez-Gonzalez A and Battaglia P W 2021 Learning mesh-based simulation with graph networks *International Conference on Learning Representations (ICLR)*
- [40] Lewis P, Perez E, Piktus A *et al* 2020 Retrieval-augmented generation for knowledge-intensive NLP tasks *Advances in Neural Information Processing Systems (NeurIPS)* vol 33
- [41] Yao S, Zhao J, Yu D, Du N, Shafran I, Narasimhan K and Cao Y 2023 ReAct: Synergizing reasoning and acting in language models *International Conference on Learning Representations (ICLR)*
- [42] Johnson J, Douze M and Jégou H 2019 Billion-scale similarity search with GPUs *IEEE Transactions on Big Data* **7** 535–547

- [43] Rahman M 2026 Physically interpretable AlphaEarth foundation model embeddings enable LLM-based land surface intelligence *Remote Sensing Applications: Society and Environment* **42** 102045
- [44] Rahman M, Barrett S J and Last C 2026 Characterizing AlphaEarth embedding geometry for agentic environmental reasoning *arXiv preprint arXiv:2604.18715* Under review at Environmental Data Science
- [45] Rahman M 2026 Sensor-specialized JEPA foundation models complement planetary-scale embeddings for agentic hydrologic reasoning *Remote Sensing Applications: Society and Environment* **43** 102136
- [46] Sommers A, Meyer C, Morlighem M, Rajaram H, Poinar K, Chu W and Mejia J 2023 Subglacial hydrology modeling predicts high winter water pressure and spatially variable transmissivity at Helheim Glacier, Greenland *J. Glaciol.* 1–13
- [47] Sommers A, Meyer C, Poinar K, Mejia J, Morlighem M, Rajaram H, Warburton K and Chu W 2024 Velocity of Greenland’s Helheim Glacier controlled both by terminus effects and subglacial hydrology with distinct realms of influence *Geophysical Research Letters* **51** e2024GL109168
- [48] Meyer C R, Warburton K L, Sommers A N and Minchew B M 2026 A model of water extraction from the subglacial hydrologic system under idealized conditions *The Cryosphere* **20** 2659–2680
- [49] Thota V K, Vijay S, Sommers A N, Banerjee A, Mey J and Motagh M 2026 Seasonal variability in ice velocity driven by subglacial hydrology of drang drung glacier, western himalayas *Journal of Glaciology* **72** e44
- [50] Narayanan N G, Sommers A N, Chu W, Steiner J F, Siddique M A, Meyer C R and Minchew B 2025 Simulating seasonal evolution of subglacial hydrology at a surging glacier in the karakoram *Journal of Glaciology* **71** e94
- [51] Azam M F, Hussain M A, Kaushik H, Srivastava S, Munda M K, Mandal A, Bahuguna I, Singh S K and Jawad M 2025 Initial glaciological investigations on a large himalayan glacier: Drang drung (zanskar, ladakh, india) *Journal of Glaciology* **71** e56
- [52] Singh P, Vijay S and Azam M F 2026 High-frequency observation of glacier ice velocities at drang drung glacier, western himalaya, using a terrestrial time-lapse imaging system *Science of Remote Sensing* 100431
- [53] Millan R, Mouginot J, Rabatel A and Morlighem M 2022 Ice velocity and thickness of the world’s glaciers *Nature Geoscience* **15** 124–129
- [54] Dias dos Santos T, Morlighem M and Brinkerhoff D 2022 A new vertically integrated mono-layer higher-order (molho) ice flow model *The Cryosphere* **16** 179–195
- [55] Morlighem M *et al* 2021 IceBridge BedMachine Greenland, version 4 [data set] *NASA National Snow and Ice Data Center Distributed Active Archive Center*
- [56] MacAyeal D R 1989 Large-scale ice flow over a viscous basal sediment: theory and application to Ice Stream B, Antarctica *Journal of Geophysical Research: Solid Earth* **94** 4071–4087
- [57] GMAO 2015 Merra-2 tavg1.2d.lnd.nx: 2-d, 1-hourly, time-averaged, single-level, assimilation, land-surface diagnostics v5.12.4