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Multi-sphere coupled evolution of glacial lake outburst flood disasters under climate change: A complex network perspective

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In high mountain cold regions, accelerated glacier retreat has increased the frequency of glacial lake outburst floods (GLOFs). Under climate change, GLOFs are no longer isolated events[1] but systemic disaster chains arising from the deep coupling of cryospheric, hydrological, geological, and socio-economic spheres. However, conventional hazard assessments based on linear causality or static indicators are less effective in capturing the non-linear amplification and cross-scale feedbacks in these multi-sphere cascading processes. In this commentary, a physics-informed complex network framework is proposed to mathematically characterize the coupled mass and energy transmission across spheres. This approach offers a computationally efficient paradigm for rapid GLOF disaster modeling, early warning, and prediction in high mountain catchments.

LIMITATIONS OF CONVENTIONAL APPROACHES IN A CHANGING HAZARD REGIME

Beyond the limitations of using linear causality and static indicators, traditional models suffer from severe computational bottlenecks. While highly accurate, reproducing the full, multi-sphere hazard chain from ice avalanches and surge waves to breach and sediment-laden debris flows requires hours of computation,[2] making emergency forecasting prohibitive. Consequently, these models are unsuitable for representing multi-sphere interactions and feedbacks. Furthermore, traditional assessments pay limited attention to the topology of the broader socio-economic system and fail to illustrate how hazard impacts propagate dynamically through downstream communities.

To overcome these limitations, a complex network framework maps continuous hydrodynamic fields into discrete topological relationships, representing multi-source triggers (e.g., glacier melt, slope failure, rainfall) and downstream impacts as a unified, coupled system. Utilizing network topological metrics such as betweenness centrality and clustering coefficient, the framework identifies "hazard amplifiers" driven by multi-sphere interactions and topological signs of critical phase transitions, enabling rapid risk propagation modeling and prediction.

TOPOLOGICAL MAPPING RULES AND PHYSICAL-STRUCTURAL NETWORK CONSTRUCTION

In the complex network framework, GLOF processes are mapped onto a weighted graph structure comprising nodes (V) and edges (E). The nodes are categorized into source nodes (e.g., glaciers V_G, slopes V_M, precipitation V_P), channel-barrier nodes (e.g., lake V_L, lake dam V_D, downstream debris V_R), and sink nodes (e.g., socio-economic assets V_A). Edges indicate the pathways along which physical mass/energy is transferred. For example, the glacier-to-lake edge $E(V_G \rightarrow V_L)$ represents glacier meltwater or calving ice entering the lake, while the precipitation-to-dam edge $E(V_P \rightarrow V_D)$ represents rainfall-induced seepage. Edge weights (W) between connected nodes are quantified by physical processes. For instance, the weight of $E(V_G \rightarrow V_L)$ is determined by combining satellite-derived glacier velocity and glacio-hydrological runoff modeling, whilst downstream impact edges $E(V_R \rightarrow V_A)$ are weighted by monitored or simulated water depths and flow velocities. Traditional physical models calculate microscopic states to dynamically assign edge weights during the graph initialization stage.

Based on this weighted topology, GLOF disaster phases are then diagnosed using node-level network metrics. Specifically, in-degree centrality (kin) of any node physically quantifies cumulative mass or energy load entering from upstream; a continuous increase in kin indicates rapid hazard incubation. Simultaneously, the local clustering coefficient (C) measures the structural coupling density and synchronization readiness among multi-source triggers, serving as an early warning of shifts to a highly sensitive state. Furthermore, betweenness centrality (g) identifies critical "hazard amplifiers" where mass accumulation can trigger secondary outburst floods.

NETWORK DYNAMICALLY GROWING AND CRITICAL TRANSITIONS

Under climate change, the GLOF network grows dynamically, driving topological transitions and rewiring. During incubation, lake expansion and slope destabilization are monitored via cumulative node load over time, represented by increasing edge inputs (Eq.1).

$$L(VL,t) = L(VL,0) + \int_0^t [fmelt(\tau) + fprecip(\tau) + Qnet(\tau)]d\tau \quad (1)$$

where $L(V_L,t)$ is lake load, $f_{melt}(\tau)$ is the temperature-driven melt, $f_{precip}(\tau)$ is rainfall, and $Q_{net}(\tau)$ is net mass input of the lake. When load exceeds the dam's capacity, the dam node undergoes a state phase transition (failure), triggering the topological transition from incubation to outburst phase, instantly activating downstream propagation pathways.

During propagation, downstream channel nodes (V_R) and geomorphological chokepoints (V_{choke}) are sequentially activated, with flow depth and velocity dynamically updated (Eq. 2).

$$F_{V_R,t} = F_{V_R,t-\Delta t} + \left(\sum \mu_{in} \times F_{E(V_{in} \rightarrow V_R),t} - \sum \mu_{out} \times F_{E(V_R \rightarrow V_{out}),t}\right) \quad (2)$$

where μ is the weight quantifying contributions of individual edges to the connected node V_R, which is dynamically updated by $L(Vi,t)$, $L(Vj,t)$, fluid density(ρ_{ij}), and topographic slope (τ_{ij}) along the active edge $E(V_i \rightarrow V_j)$.

Additionally, climate change forces the formation of new unstable nodes and edges, which should be updated in the network. For instance, rising temperatures increase meltwater edges and destabilize slopes. The spatiotemporal synchronization of rapid glacier melting, slope degradation, and intense rainfall increases the local clustering coefficient and node loads, pushing the network toward rapid phase transitions.

MULTI-SPHERE COUPLING ACROSS PHYSICAL AND SOCIAL LAYERS

During the incubation and triggering phase, the atmosphere connects to the cryosphere and hydrosphere. Warming and extreme rainfall accelerate glacier retreat and destabilize slopes, triggering ice avalanches into the lake. This physical cascade is represented by a sharp surge in edge weights $E(V_P \rightarrow V_M)$ and $E(V_M \rightarrow V_L)$, reflecting rapid mass accumulation before breaching.

During propagation, the hydrosphere connects to the geosphere. Upon dam breaching, the suddenly released floodwaters entering downstream channels (V_R) scour the valley, entraining sediment into high-density debris flows through narrow chokepoints, resulting in rising node loads.

Finally, the geosphere connects to the anthroposphere during the impact phase, propagating physical disasters into human society.[3] Three layers are coupled via geomorphological overlap edges $E(V_R \rightarrow V_A)$: physical hazard layer (inundation nodes), critical infrastructure layer (e.g., roads, bridges), and socio-economic layer (e.g., settlements, shelters). A weighted physical hazard node triggers adjacent infrastructure failure via vulnerability functions and thresholds. This failure propagates to the social layer, causing disconnection of critical

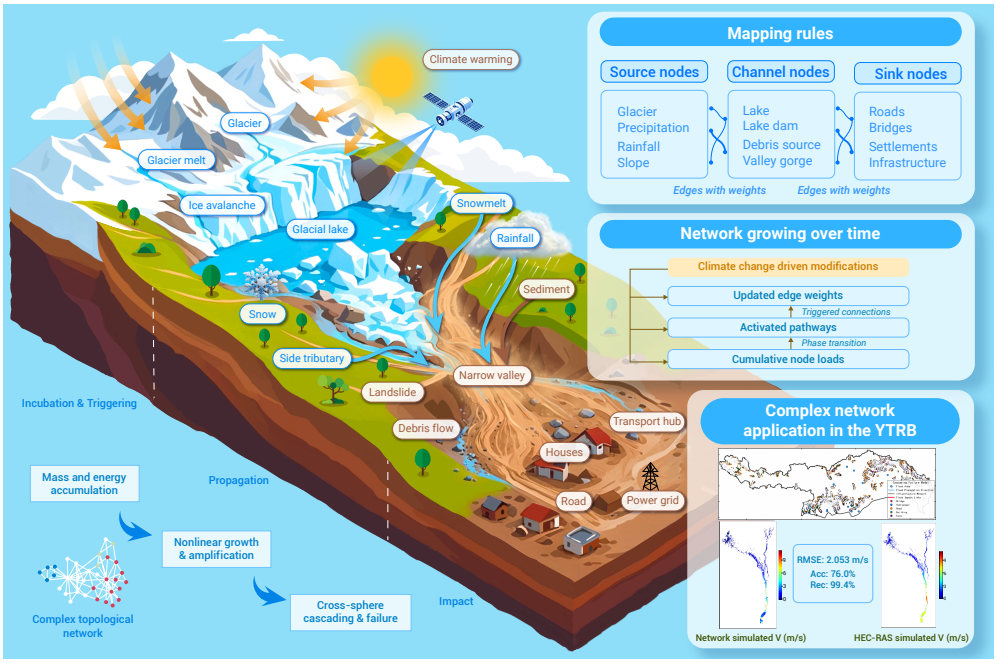


Figure 1. Architecture of the glacial lake outburst flood (GLOF) disaster system based on complex network theory The complex network model maps GLOF processes onto a graph structure, representing the coupled mass and energy transmission across multi-sphere, and is applied to GLOF propagation modeling in the Yarlung Tsangpo River Basin (YTRB).

roads or power lines to emergency shelters, dynamically quantifying community isolation.

BASIN-SCALE VALIDATION AND DYNAMIC PROCESS CHAIN REPRESENTATION

To demonstrate physical validity of the network framework, a basin-scale validation was conducted in the Yarlung Tsangpo River Basin using 449 modeled GLOF events.[2] Digital elevation models (DEMs), land-use maps, and local exposure datasets including bridges, farms, hydropower stations, and buildings were integrated. The physical hydrodynamic processes simulated by HEC-RAS were coupled with these socio-economic networks via spatial-functional mapping interfaces, yielding a multi-layer network of 54,903 flood nodes, 92,275 infrastructure nodes, and 66,476 impact edges. A hybrid Graph Neural Network (GNN) and Transformer-based surrogate model was constructed to learn the non-linear spatiotemporal propagation dynamics. The topology-based surrogate model achieved high agreement with the physical HEC-RAS simulations (utilized only for the graph initialization stage), predicting flow velocities with an average RMSE of 2.1 m/s and a capture accuracy of 89%. Crucially, simulation times for complex cascade propagation were reduced from hours in traditional physical models to seconds across all 449 events, proving the framework's scalability for rapid GLOF modeling and prediction. Based on this validated propagation framework, a prospective early-warning system is conceptually proposed, utilizing node *kin*, local *C*, and *g* to dynamically characterize lake load, trigger pathways, and systemic collapse as described in topological mapping rules and physical-structural network construction.

CHALLENGES, LIMITATIONS AND FUTURE OUTLOOK

While the complex network approach provides a transformative paradigm for rapid GLOF modeling and prediction, offering significant pathways for targeted early warning and risk reduction,[4] several limitations must be acknowledged. First, network topology is highly sensitive to graph modeling choices, discretization scales, and data uncertainties. Second, topological importance characterized by high betweenness or in-degree centrality does not automatically equate to physical causality, which must always be verified against physical-process understanding before practical implementation. Third, network discretization can miss fine-grained hydrodynamic details, underscoring the necessity of a hybrid modeling approach that couples network topology with traditional physical models.

Beyond these limitations, three key challenges must be addressed. First challenge is the fusion of multi-source heterogeneous data for rapid network reconstruction in data-scarce regions,[5] requiring methods to infer dynamic structures from remote sensing and reanalysis data. Second is achieving deeper coupling among multi-physics fields by embedding complex differential process representations into node-level rules. Third involves the scale mismatch between physical and social spheres, where physical processes follow continuum mechanics while social processes are expressed through discrete behaviors. Future risk assessments should use multilayer approaches to explore optimal configurations of infrastructure and community organization to enhance systemic resilience.

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AUTHOR CONTRIBUTIONS

Z. H. and X. M. conceived the commentary and prepared the manuscript. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.