Investigating High-Latitude Permafrost Carbon Dynamics with Artificial Intelligence and Earth System Data Assimilation

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Abstract

It is well-established that positive feedbacks between permafrost degradation and the release of soil carbon into the atmosphere impacts land-atmosphere interactions, disrupts the global carbon cycle, and accelerates climate change. The widespread distribution of thawing permafrost is causing a cascade of geophysical and biochemical disturbances with global impact. Currently, few earth system models account for permafrost carbon feedback mechanisms. This research identifies, interprets, and explains the feedback sensitivities attributed to permafrost degradation and terrestrial carbon cycling imbalance with in situ and flux tower measurements, remote sensing observations, process-based modeling simulations, and deep learning architecture. We defined and formulated high-resolution polymodal datasets with multitemporal extents and hyperspatiospectral fidelity (i.e., 12.4 million parameters with 13.1 million in situ data points, 2.84 billion ground-controlled remotely sensed data points, and 36.58 million model-based simulation outputs to computationally reflect the state space of the earth system), simulated the non-linear feedback mechanisms attributed to permafrost degradation and carbon cycle perturbation across Alaska with a process-constrained deep learning architecture composed of cascading stacks of convolutionally layered memory-encoded recurrent neural networks (i.e., GeoCryoAI), and interpreted historical and future emulations of freeze-thaw dynamics and the permafrost carbon feedback with a suite of evaluation and performance metrics (e.g., cross-entropic loss, root-mean-square deviation, accuracy). This framework introduces ecological memory components and effectively learns subtle spatiotemporal covariate complexities in high-latitude ecosystems by emulating permafrost degradation and carbon flux dynamics across Alaska with high precision and minimal loss (RMSE: 1.007cm, 0.694nmolCH₄m⁻²s⁻¹, 0.213μmolCO₂m⁻²s⁻¹). This methodology and findings offer significant insight about the permafrost carbon feedback by informing scientists and the public on how climate change is accelerating, strategies to ameliorate the impact of permafrost degradation on the global carbon cycle, and to what extent these connections matter in space and time.
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BACKGROUND

Frozen soil and carbon-rich permafrost characterizes approximately 14 million square kilometers globally, with soil organic carbon stocks estimated at 130±170 Pg C (Hugelius et al., 2014). Thaw-induced carbon release is a climate change catalyst and when coupled with anthropogenic-induced warming triggers acceleration, and sustain a positive nonlinear carbon-climate feedback for hundreds of thousands of years (Schuur et al., 2015). The variability of thaw climate feedback for hundreds of thousands of years induced carbon release is a climate change catalyst for hundreds of thousands of years (Li et al., 2017; Randall et al., 2007).

Due to spatiotemporal limitations, instrument constraints, and other challenges in the high latitudes (e.g., frequent cloud cover, short summer periods, low illumination), the ability to quantify or infer thaw variability with high confidence is restricted with remote sensing platforms (Gay, 2023; Esa et al., 2023). Moreover, subroutines and interactions governing earth system models vary widely, often overlapping the dynamics and long-term impacts of the PCF (Li et al., 2017; Randell et al., 2007).

Fortunately, artificial intelligence (AI) optimizes complex earth system data processing, captures nonlinear relationships, and improves model skill and uncertainty quantification.

MOTIVATION

This study leverages a hybridized multimodal ensemble learning formulation (GeoCryoAI) with site-level in situ measurements, remote sensing observations, and modeling outputs across the tundra and boreal landscapes in Alaska. The objective is to disentangle the drivers of change by constraining, scaling, and simulating the climate factors contributing to the PCF signal to better understand periglacial processes, carbon-climate interactions, biogeophysical relationships, and the hidden determinants of ecological memory in the high latitude earth system.

RESULTS

Evaluation of time-delayed native persistence and GeoCryoAI simulations yielded the following error metrics (RMSE) with loss functions and predictions illustrated in the plots below:

- GeoCryoAI: 0.715nmolCH₄/m²/s (2011-2022)
- CO₂: 1.966molCO₂/m²/s, 0.879pmolCO₂/m²/s

After transformation, dimensionality reduction, trend removal, time-delayed supervision, and regression analyses, model training initialized 2.51M parameters and high dimensional, time-variant multimodal datasets, e.g., 13.1M in situ measurements, 8.06B airborne observations, 7.48B model outputs.

The GeoCryoAI architecture is constructed with stacked convolutionally-layered memory-encoded recurrent neural networks optimized with a hyperparameter dictionary and a Bayesian Optimization search algorithm. Feedback nonlinearities are emulated with ground truth teacher forcing and module reconstruction functions (i.e., consolidated tabular time-series layer processing and sequential time-distributed convolving layers).

SIGNIFICANCE AND FUTURE WORK

This study underscores the significance of thaw-induced climate change exacerbated by the PCF and highlights the importance of resolving the spatiotemporal variability of ALT as a sensitive harbinger of change. Ongoing research elucidates on the PCF and delayed subsurface phenomena by (1) expanding the flexibility and knowledge base of the model with current and future scenarios to reference past and improved performance (e.g., AVIRIS-NG, UAVSAR, TROPOMI, PREFIRE, NISAR, CRYSTAL; UAS DSMs; TIR), and (2) generating temporal and spatial time maps to distributes to the State of AK, First Nation/Native Corporations, and the USGS as a JPL-led first-order effort to engage leadership and identify cross-sector risks at local, state, regional, and global levels (e.g., critical infrastructure damage, disturbance tipping points, cultural vulnerabilities). Datasets, code, and notebooks are distributed in a GitHub repository.

PUBLICATIONS | ACKNOWLEDGEMENTS


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