Decoding the Spatiotemporal Complexities of the Permafrost Carbon Feedback with Multimodal Ensemble Learning

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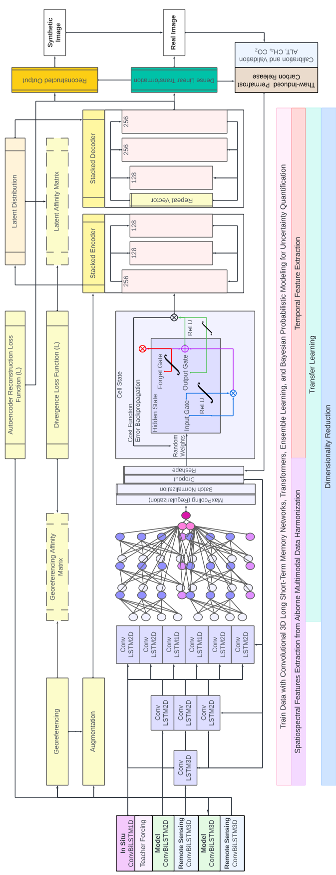
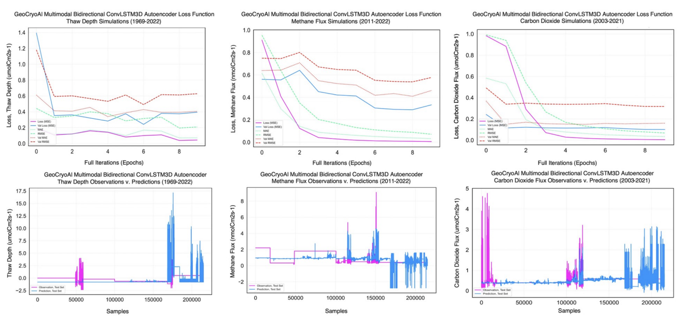
Science Question: How do the nonlinear dynamics of permafrost degradation and the permafrost carbon feedback (PCF) in Alaska respond to environmental change, and how can artificial intelligence (GeoCryoAI) enhance the modeling and understanding of these complex interactions while reconciling the data dichotomy problem?

Approach: We quantify nonlinear dynamics of the permafrost carbon feedback and reconcile the multimodal data dichotomy with artificial intelligence (AI). We address these challenges using GeoCryoAI, an AI-driven model that simultaneously ingests and analyzes disparate data types to provide estimates of the state of permafrost and the associated cycling of CH_4 and CO_2 flux.





	ALT	CH_4	CO_2
	cm	nmol CH^4 km^{-2} $month^{-1}$	µmol CO^2 km^{-2} $month^{-1}$
	1800-2100	1996-2022	1996-2022
Naïve Persistence Model			
Test RMSE	1.997	0.884	1.906
GeoCryoAI | Teacher Forcing			
Test RMSE	1.327	0.715	0.697
Fractional Reduction RMSE	-33.55%	-19.12%	-63.43%
GeoCryoAI | Multimodality			
Test MAE	0.708	0.591	0.090
Test MSE	1.014	0.481	0.045
Test RMSE	1.007	0.694	0.213
Fractional Reduction RMSE	-24.11%	-2.94%	-69.44%

Results: The GeoCryoAI model improved predictive accuracy of ALT variations and spatiotemporal forecasting of CH_4 and CO_2 flux while providing enhanced spatiotemporal resolution in characterizing PCF dynamics. GeoCryoAI successfully captured abrupt thaw events and persistent trends that were previously underrepresented in Earth system models. Revelations displayed CH_4 and CO_2 emissions were higher in wetter permafrost areas and lower in dry upland regions. The optimized GeoCryoAI framework substantially improves the efficiency, scalability, and precision of simulating the PCF; namely, it enhances the ability to predict long-term permafrost stability and the associated release of CH_4 and CO_2.

Significance: Our study establishes a new methodology for assimilating multimodal data across different observational platforms. We demonstrate the effectiveness of AI-driven ensemble learning frameworks in modeling complex permafrost-climate interactions. Our findings bridge gaps in Earth system models by integrating real-world data with AI-driven simulations, informing global climate policy.

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ABSTRACT

Complex nonlinear relationships exist between the permafrost thermal state, active layer thickness, and terrestrial carbon cycle dynamics. In Arctic and boreal Alaska, significant uncertainties characterize the spatiotemporal rate and magnitude of permafrost degradation and the permafrost carbon feedback, with increasing recognition of the importance of thawing mechanisms. The challenges of monitoring sub-surface phenomena with remote sensing technology further complicate the issue. There is an urgent need to understand how and to what extent thawing permafrost destabilizes the carbon balance in Alaska and to characterize the feedback involved. In this research, we use our artificial intelligence-driven model GeoCryoAI to quantify permafrost carbon dynamics in Alaska. The GeoCryoAI model uses a hybridized process-constrained ensemble learning framework to simultaneously ingest, scale, and analyze in situ measurements, remote sensing observations, and process-based modeling outputs with disparate spatiotemporal sampling and data densities. We evaluated prior naïve (a) persistence and (b) teacher forcing approaches relative to (c) time-delayed GeoCryoAI simulations, yielding the following error metrics (RMSE) for active layer thickness (ALT), methane (CH4), and carbon dioxide (CO2), respectively: 1.997, 1.327, 1.007 cm [1963–2022]; 0.884, 0.715, 0.694 nmol CH4km−2 month−1 [1994–2022]; 1.906, 0.697, 0.213 μmol CO2km−2 month−1 [1994–2022]. Our approach overcomes traditional model inefficiencies and resolves spatiotemporal disparities. GeoCryoAI captures abrupt and persistent changes while introducing a novel methodology for assimilating contemporaneous information at various scales. We describe GeoCryoAI, the methodology, our results, and plans for future applications.

SCIENTIFIC SIGNIFICANCE, SOCIETAL RELEVANCE, AND RELATIONSHIPS TO FUTURE MISSIONS

The study introduces GeoCryoAI as a scalable and efficient AI-driven framework for processing large-scale environmental data. GeoCryoAI is a hybridized ensemble learning architecture with stacked convolutional layers and memory-encoded recurrent neural networks. This study represents a significant advancement in the integration of AI with permafrost research, providing improved predictive capabilities and refining our understanding of the permafrost carbon feedback system while also highlighting the necessity for improved monitoring and mitigation strategies in Arctic and boreal regions. Furthermore, the integration of remote sensing data allowed for better quantification of carbon emissions hotspots and their spatial distribution.

AWARD INFORMATION

This research was supported by an appointment to the NASA Postdoctoral Program at the Jet Propulsion Laboratory, California Institute of Technology, administered by Oak Ridge Associated Universities. NASA Jet Propulsion Laboratory operates under a contract with the National Aeronautics and Space Administration (80NM0018D0004).

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DATA SOURCES

In Situ Measurements: ALT measurements from borehole temperature data, mechanical probing, and ground-penetrating radar (ITEX; CALM; ReSALT; SMALT-STDM). CH_4 and CO_2 flux measurements were derived from the AmeriFlux and NEON flux tower networks.
Remote Sensing Observations: Synthetic Aperture Radar (SAR) from UAVSAR for measuring surface deformation and thaw subsidence. Imaging spectroscopy from AVIRIS-NG for detecting CH_4 and CO_2 emissions from permafrost degradation. Reanalysis climate data from ERA5 to contextualize atmospheric conditions and boundary layer dynamics.
Process-Based Modeling (PBM) Outputs: SIBBORK-TTE model for simulating permafrost thaw and active layer depth. TCFM-Arctic model for predicting CH_4 and CO_2 emissions from Arctic permafrost.
Machine Learning and AI Framework: GeoCryoAI, an AI-driven ensemble learning model, processes and synthesizes in situ, remote sensing, and modeling data. Utilizes stacked convolutional layers and memory-encoded recurrent neural networks for long-term forecasting and simulation. Applied Bayesian optimization and regularization techniques to fine-tune model performance.

TECHNICAL DESCRIPTION OF FIGURES

The **flowchart** elements above elucidate on the data pre-processing and assimilation methodology (i.e., data cleaning, resampling, dimensionality reduction, partitioning, transformation, batching) followed by model assembly and analyses (i.e., model compilation, optimization, model fitting, inverse transformation, evaluation, prediction, uncertainty quantification, and interpretation), expanding on previous teacher forcing methods (Gay et al., 2023). The **plot panel** illustrates the loss functions, observations, and predictions for GeoCryoAI loss functions, observations, and predictions (ALT, 1969–2022; CH4, 2003–2021; CO2, 2003–2021). The **table** presents evaluation and prediction error statistics obtained during testing of the GeoCryoAI framework.