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Investigating Permafrost Carbon Dynamics in Alaska with Artificial Intelligence

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GeoCryoAI

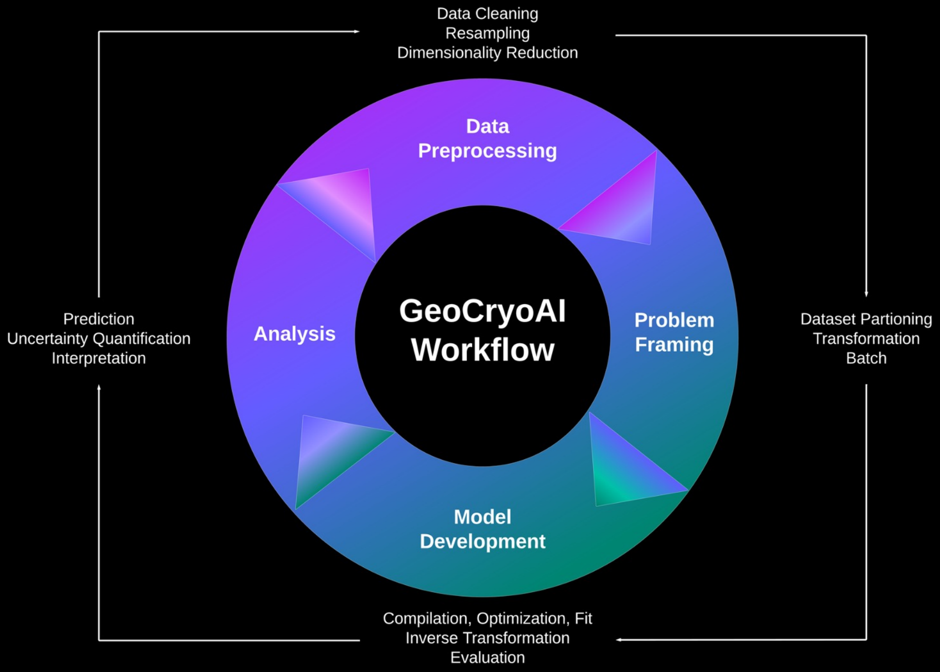
Summary of research and what application was investigated?

Problem

Reconciliation of Data Dichotomy with Artificial Intelligence

Application

Permafrost Carbon Feedback



Gay et al., 2023

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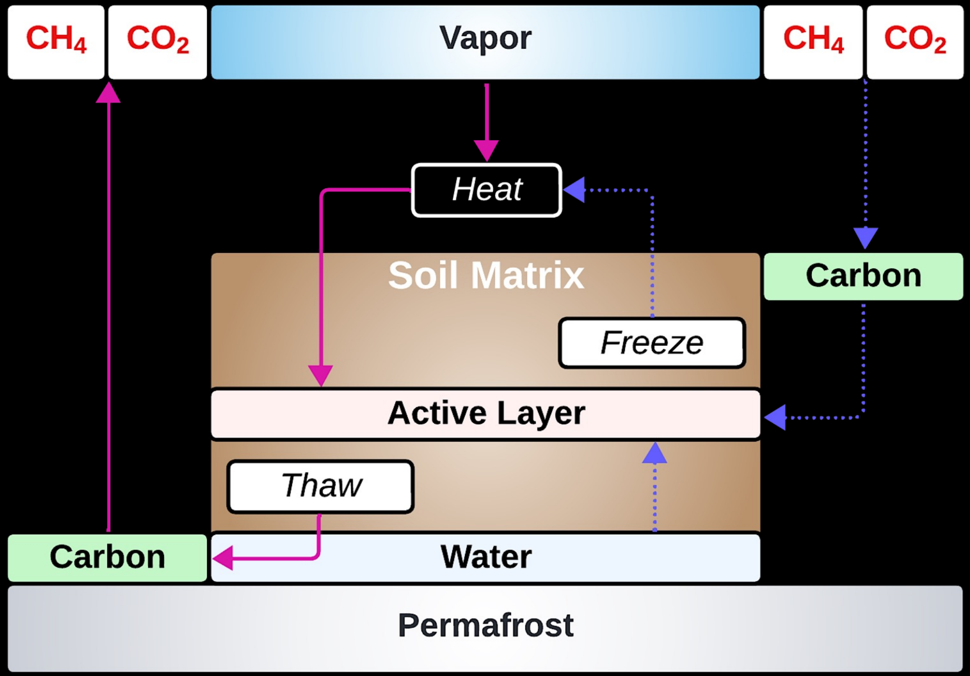
Permafrost Carbon Feedback

What is it and why is it important?

Due to climate change, rising global temperatures continue to accelerate thawing permafrost, exposing large quantities of ancient frozen carbon to microbial decomposition.

Carbon released from thawing permafrost is a climate change catalyst - and when coupled with anthropogenic-induced warming - trigger, accelerate and sustain a positive self-reinforcing nonlinear carbon-climate feedback for hundreds of thousands of years (Schuur et al., 2015).



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Permafrost Carbon Feedback

How is it a challenging problem?

- **Big Data:** Operating in a space of diametrically opposing issues, i.e., dearth of field data over space and time or an over-abundance much data acquired from remote sensing and modeling resources to store, process, and analyze.
- **Remote Sensing**: The ability to quantify or infer the magnitude, rate, and extent of the permafrost carbon feedback (i.e., thaw variability, carbon release) with high confidence across space and time is <u>restricted</u> with remote sensing platforms (Miner et al., 2021; Gay, et al., 2023; Esau et al., 2023).
- **Modeling:** Subroutines and interactions governing earth system models (ESMs) vary widely, with many overlooking the dynamics and long-term impacts of the PCF when simulating high-latitude systems (Li et al., 2017; Randall et al., 2007).

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Permafrost Carbon Feedback

What solutions help reconcile these challenges?

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

We pursued an AI approach resulting in GeoCryoAI, a multimodal hybridized ensemble learning formulation that leverages site-level *in situ* measurements, remote sensing observations, and modeling outputs across Alaska.

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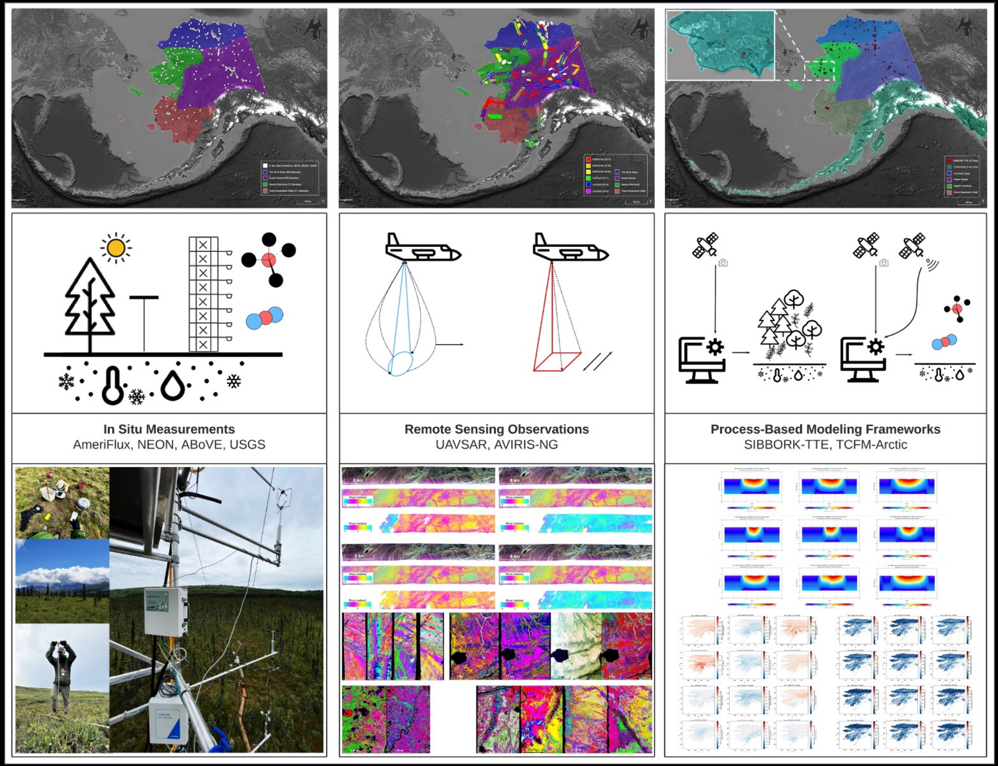
Study Domain and Data Dichotomy

The study domain consisted of Alaska (1.723M km^2) covering 26.92% of the ABoVE Domain (6.4M km^2) and 11.88% of the Arctic landscape (14.5M km^2).

After transformation, dimensionality reduction, trend removal, time-delayed supervision, and regression analyses, model training initializes 2.51M parameters and high dimensional, time-variant multimodal hyperspatiospectral datasets:

- 13.1M *in situ* measurements
- 8.06B airborne observations
- 7.48B model outputs.



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Data Dichotomy

What are the different modalities and how is scale reconciled?

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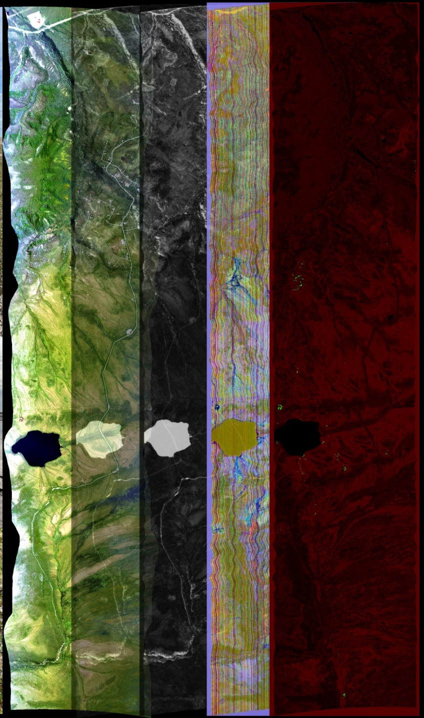
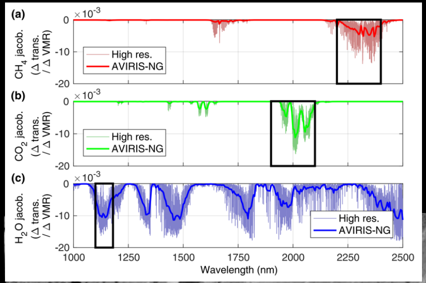
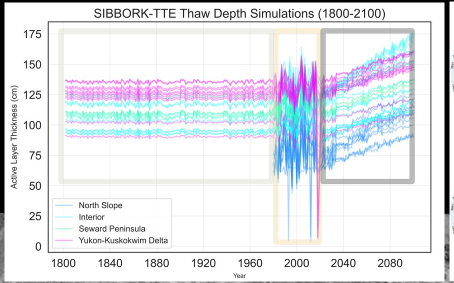
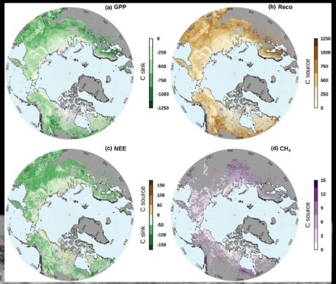


Eight Mile Lake AVng_242A-242Z_FL194 AVIRIS-NG: (RGB; 44.914 km) ang20170706t183519_rdn_v2p9



Thorpe, A.K., et al. (2017). https://doi.org/10.5194/amt-10-3833-2017





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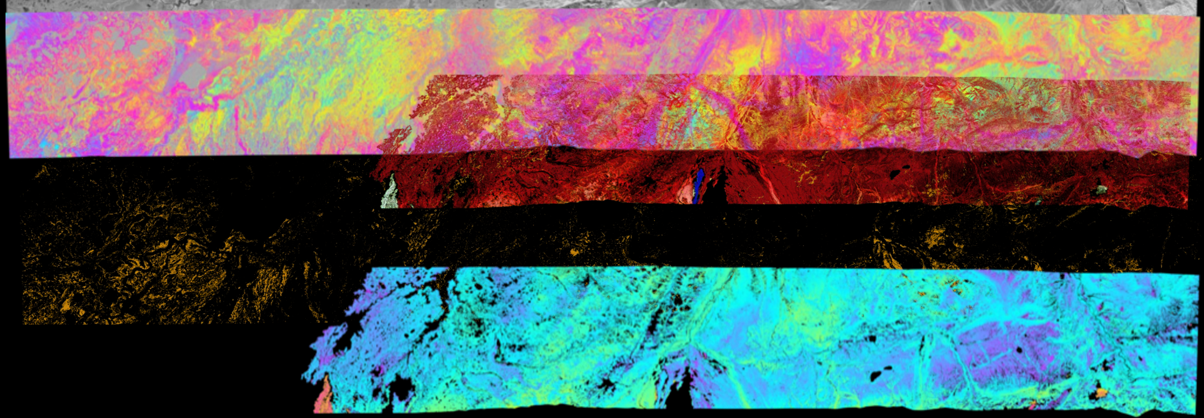
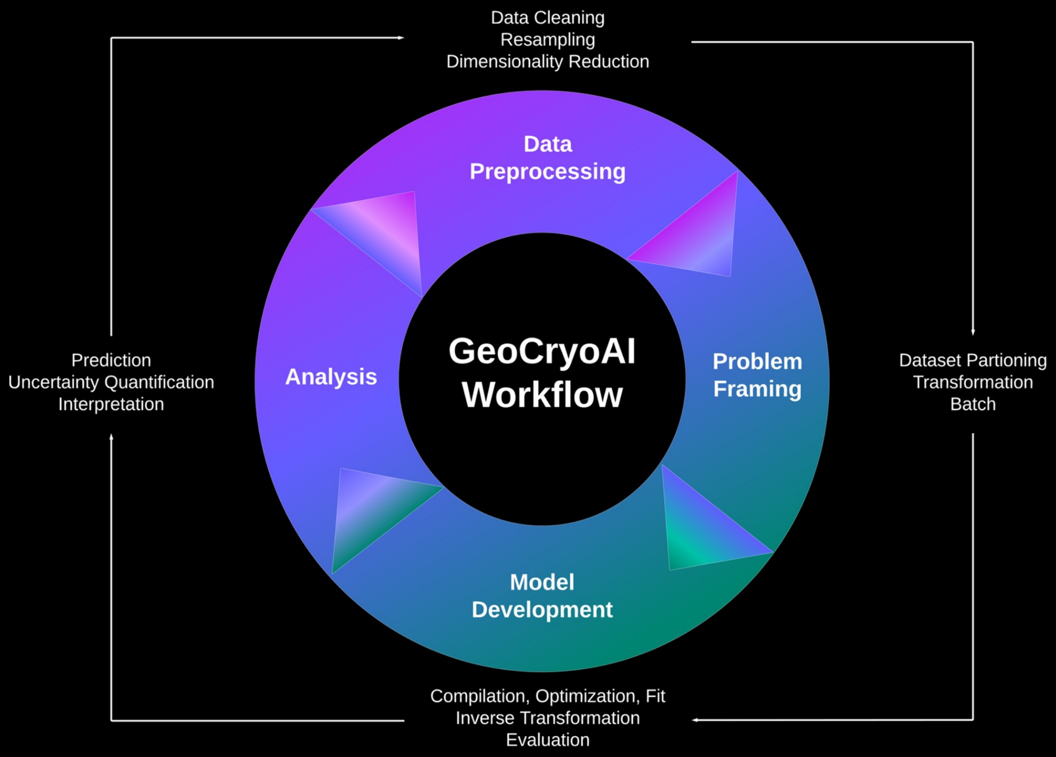


Eight Mile Lake, Denali North UAVSAR (L-band, polSAR RPI/inSAR VV/VV), 2017 July-September Δ) denalN_09115_17066-008_17100-003_0094d_s01_L090_01; 29396, 4811, 4.99m, 17-Jun-2017 22:29:35-22:41:16 UTC-19-Sep-2017 21:30:17-21:41:14 UTC, 160-km length of processing data (Linear Power, Phase Radians)

GeoCryoAI



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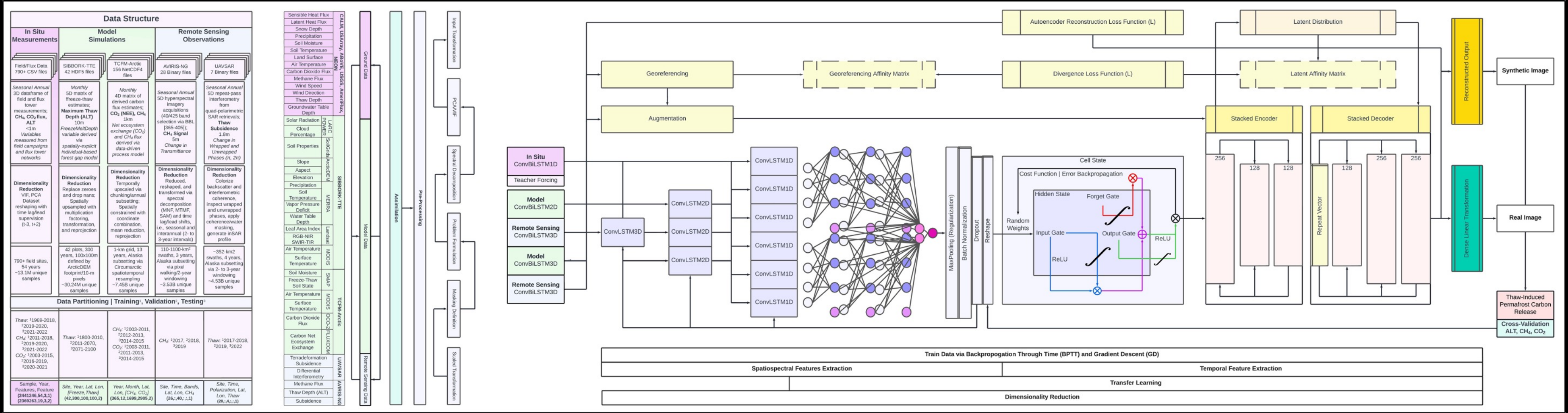
GeoCryoAI

The engine under the hood



The GeoCryoAI architecture is constructed with a process-constrained ensemble learning hybridized framework of stacked convolutionally-layered long short-term memory-encoded recurrent neural networks optimized with a hyperparameter dictionary and a Bayesian Optimization search algorithm.

$$y_{(t)} = \emptyset(W_X^T x_{(t)} + W_y^T y_{(t-1)} + b)$$

$$H_p = \underset{x \in X}{argmin}\, f(x)$$

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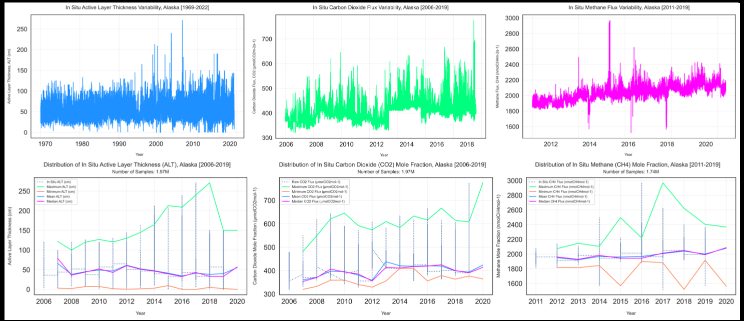
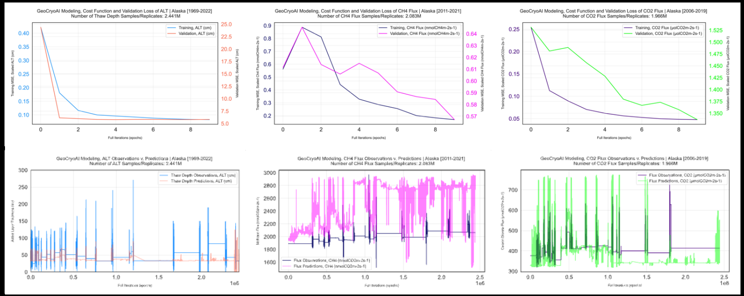
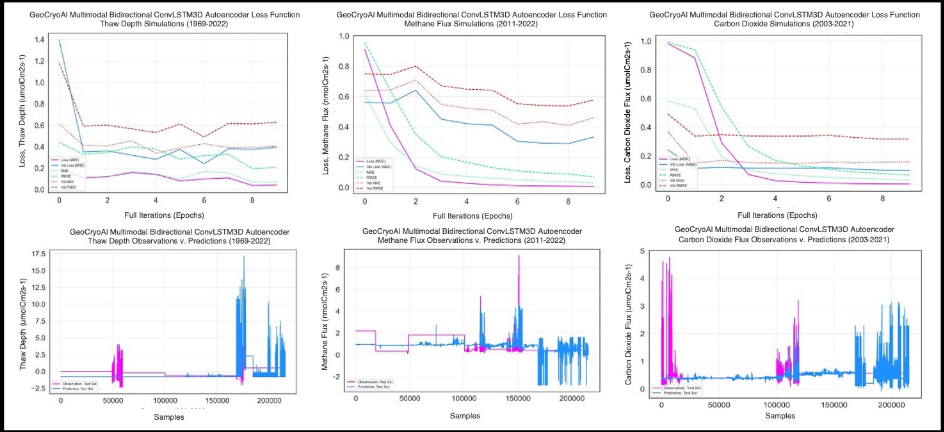
Results

Cost Functions and Performance







Loss functions and predictions derived from GeoCryoAI simulations of (L) *in situ* thaw depth and carbon release during teacher forcing and (R) multimodal thaw depth and carbon release data

	ALT (1969-2022), cm	CH_4 (2011-2022), $nmolCH_4m^{-2}s^{-1}$	CO_2 (2006-2019), $\mu molCO_2m^{-2}s^{-1}$
Naïve RMSE	2.00	0.88	1.91
GeoCryoAI RMSE	1.33	0.72	0.70
Fractional Reduction RMSE	-33.55%	-19.12%	-63.43%

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So What?

What are the contributions and limitations?

Contributions

- GeoCryoAI introduces ecological memory components of a dynamical system by effectively learning the subtle complexities among these covariates while demonstrating an aptitude for emulating permafrost degradation and carbon flux dynamics with increasing precision and minimal loss.
- These efforts provided a novel and multidisciplinary approach to constraining spatiotemporal complexities and understanding the Arctic ecosystem while refining traditional model parameterization efficiencies with state-of-the-art developments in computing and artificial intelligence.

Limitations

- The model presented minor prediction errors and exposure biases that compounded iteratively, and the teacher-forcing approach simplified the loss landscape in exchange for computational efficiency.
- The vanishing and exploding gradients presented multiple challenges throughout training, including the risk of overfitting due to model complexity (i.e., dampened with dropout generalization) and the inability to label sparse and coarse data.
- Additional uncertainty may originate from landscape-level dynamics and regional lagged effects in response to increased warming

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Summary and Significance

Does GeoCryoAI work and is it useful?

Problem: Reconciliation of Data Dichotomy with Artificial Intelligence

Application: Permafrost Carbon Feedback

GeoCryoAI ingests a <u>huge</u> amount of data (~15.7B measurements and observations) to learn, simulate, and forecast primary constituents of the permafrost carbon feedback with prognostic and retrospective capabilities.

With more gravitation towards implementing AI/ML approaches to better understand high latitude dynamics (e.g., Brovkin, Nitze, Grosse, Pastick), 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.

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Ongoing Research and Steps Forward

What is next?

Ongoing research will further elucidate on the PCF and delayed subsurface phenomena by:

- Expanding the flexibility, efficiency, and knowledge base of the model with batching pipeline and cloud computing (e.g., ADAPT) in the interest of supporting current and future missions to minimize loss and improve performance (e.g., AVIRIS-3, UAVSAR, TROPOMI, PREFIRE, NISAR, CRISTAL; SBG TIR)

- Generating Circumarctic zero-curtain space-time maps to distribute to the State of Alaska, First Nations/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).

Sentinel-5P, OCO-2, OCO-3, Sentinel-6, PREFIRE, AWS, MAIA, NISAR, CRISTAL, Harmony (Credit: eoportal, NASA JPL, NASA, ESSP, ESA)

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Acknowledgements

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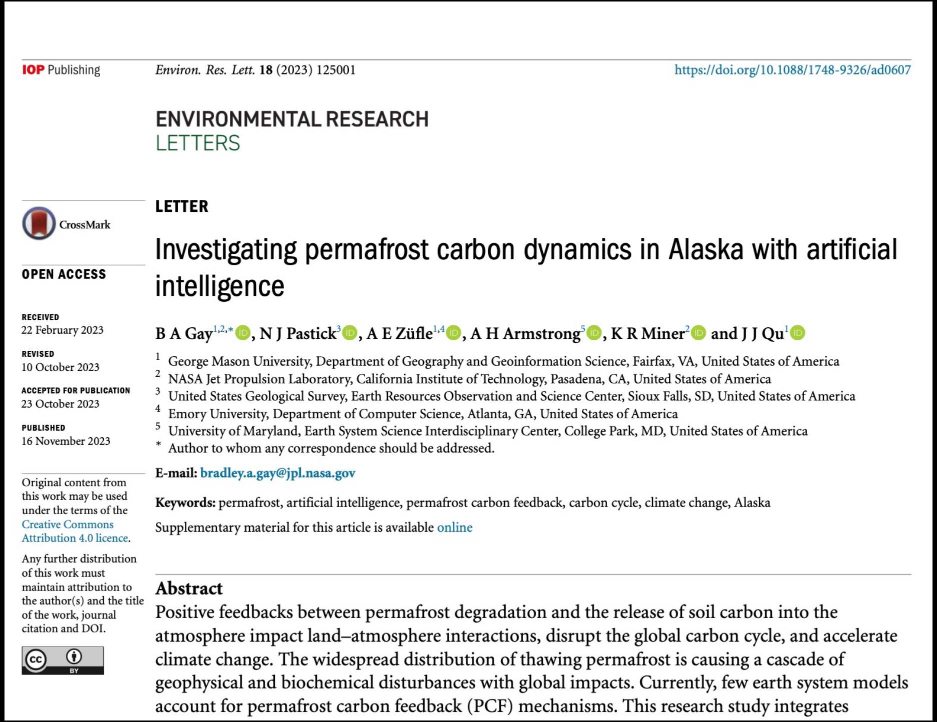
Datasets, code, and notebooks are distributed in a GitHub repository



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LETTER

Investigating permafrost carbon dynamics in Alaska with artificial intelligence

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Keywords: permafrost, artificial intelligence, permafrost carbon feedback, carbon cycle, climate change, Alaska

Supplementary material for this article is available online

Abstract

Positive feedbacks between permafrost degradation and the release of soil carbon into the atmosphere impact land–atmosphere interactions, disrupt the global carbon cycle, and accelerate climate change. The widespread distribution of thawing permafrost is causing a cascade of geophysical and biochemical disturbances with global impacts. Currently, few earth system models account for permafrost carbon feedback (PCF) mechanisms. This research study integrates

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