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CR5.8 | Understanding cryospheric processes in the past, present and future using data assimilation and machine learning

EGU24-18641 | Forecasting Permafrost Carbon Dynamics in Alaska with GeoCryoAI

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17 April 2024

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GeoCryoAI

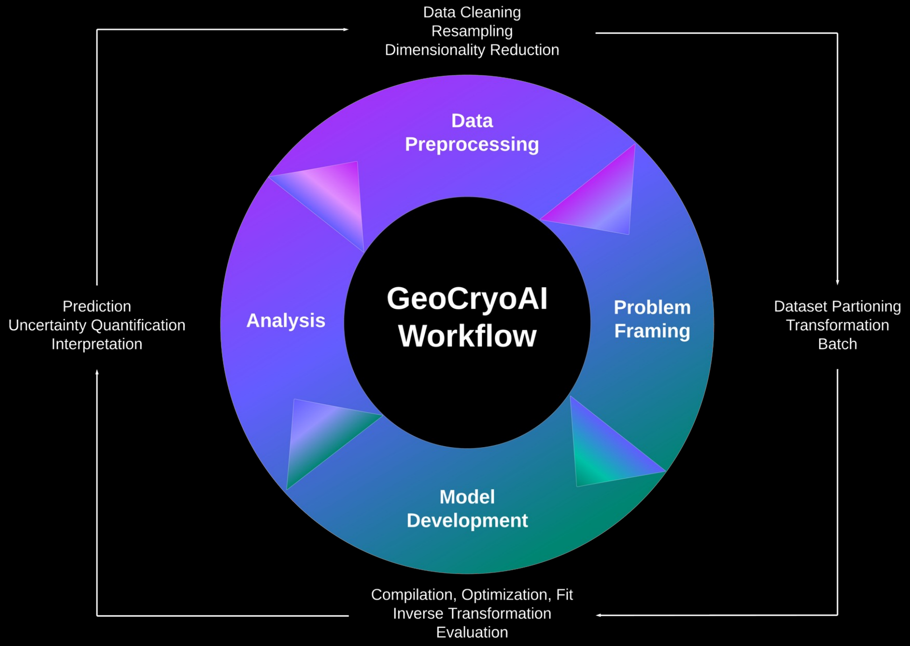
Summary of research and what application was investigated?

Problem

Reconciliation of Data Dichotomy with Artificial Intelligence

Application

Permafrost Carbon Feedback



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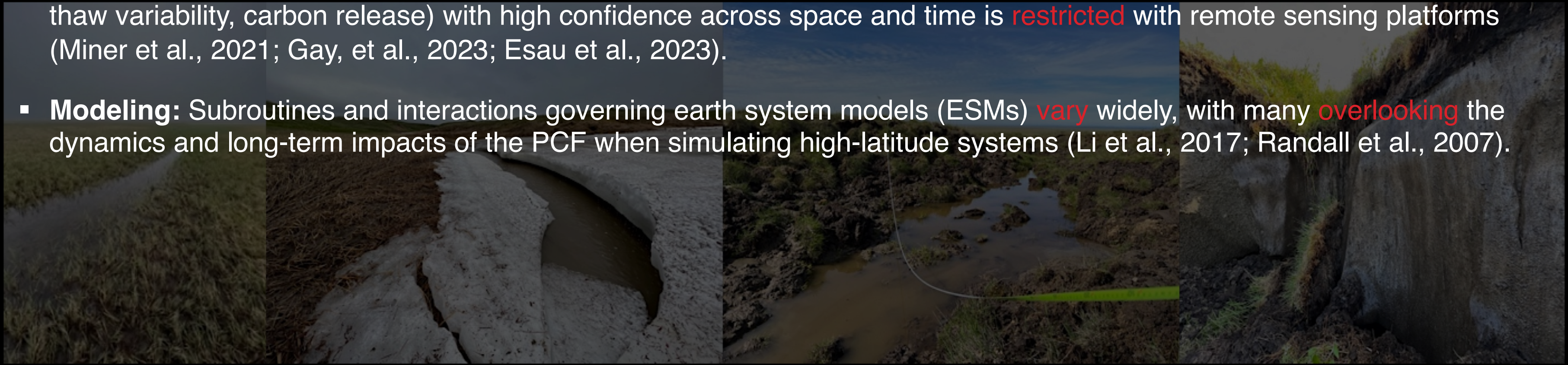
Permafrost Carbon Feedback

How is it a challenging problem?

- **Big Data:** Operating in a space of diametrically opposing issues to store, process, and analyze information over space and time, i.e., dearth of field data or an over-abundance of data acquired from remote sensing and modeling resources.

- **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 restricted 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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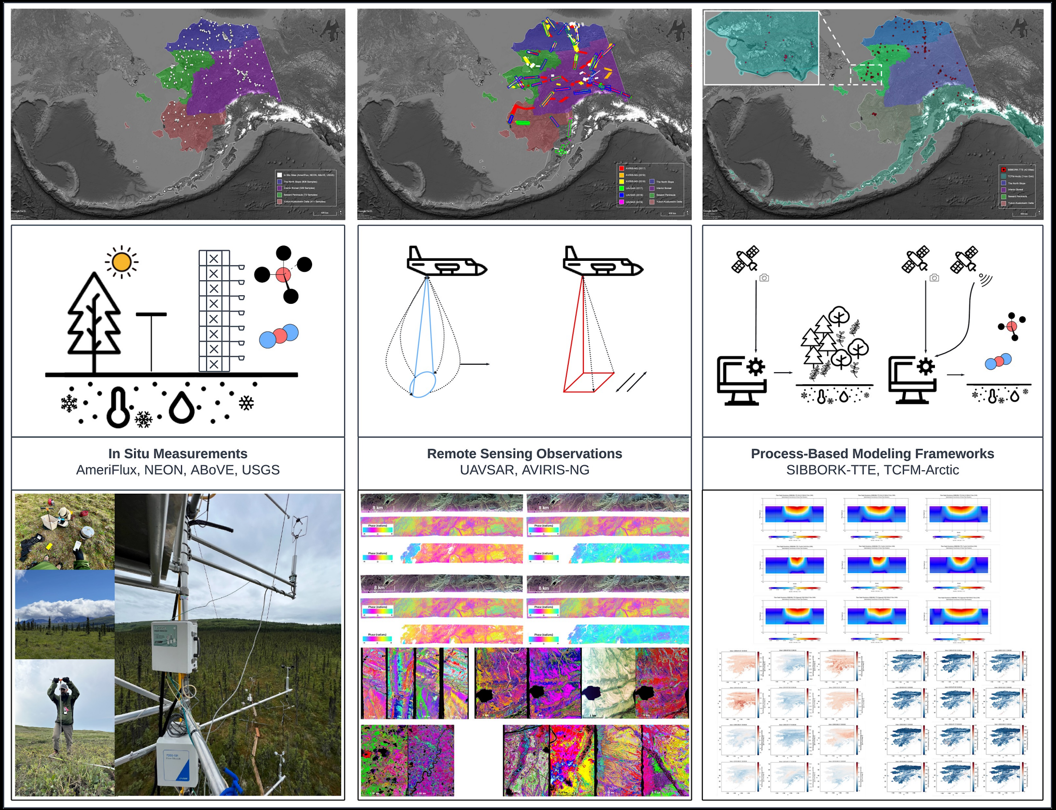
Study Domain and Data Dichotomy

The study domain consisted of Alaska (1.723M km^2), covering 26.92% of the NASA 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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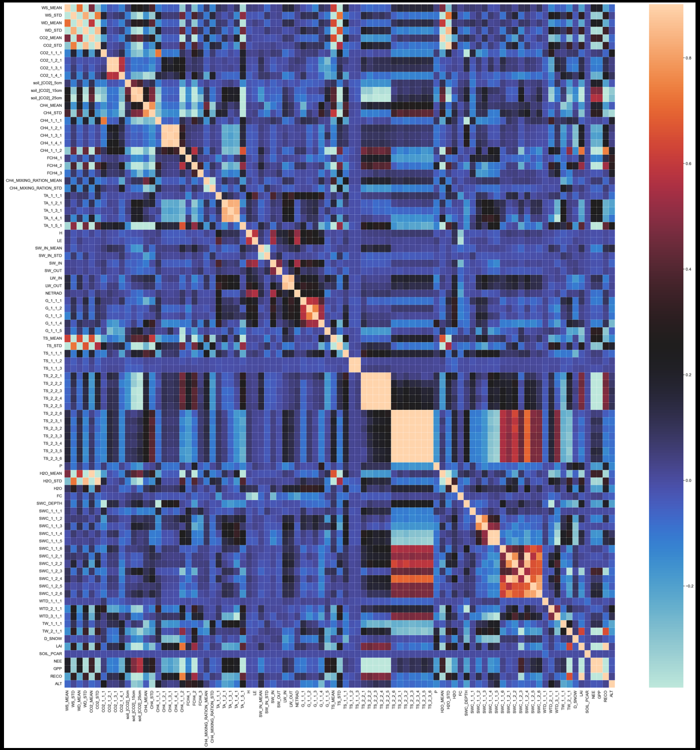
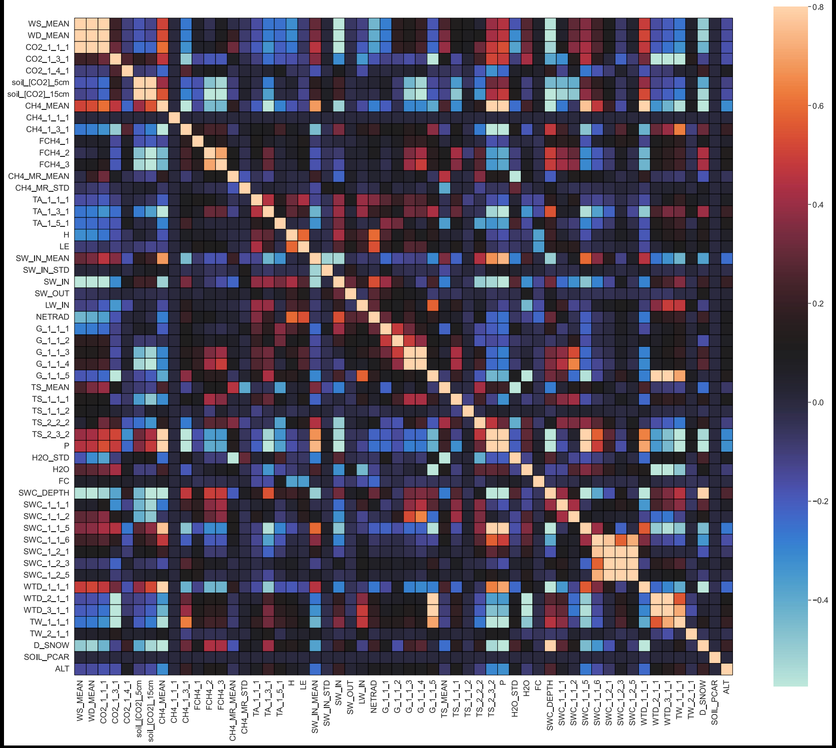
Multicollinearity





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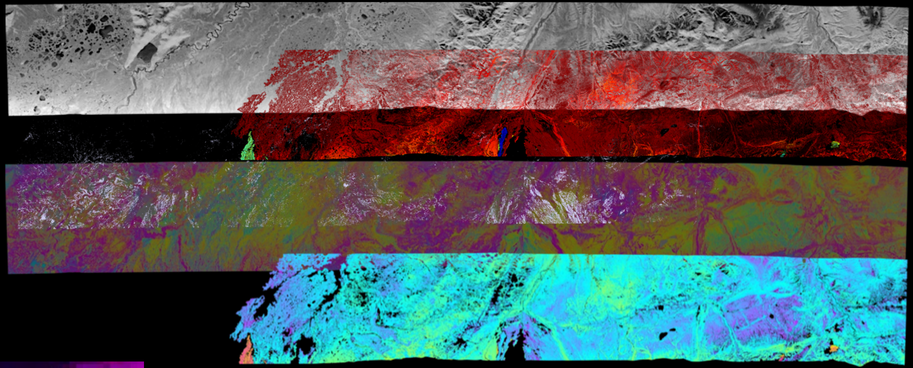
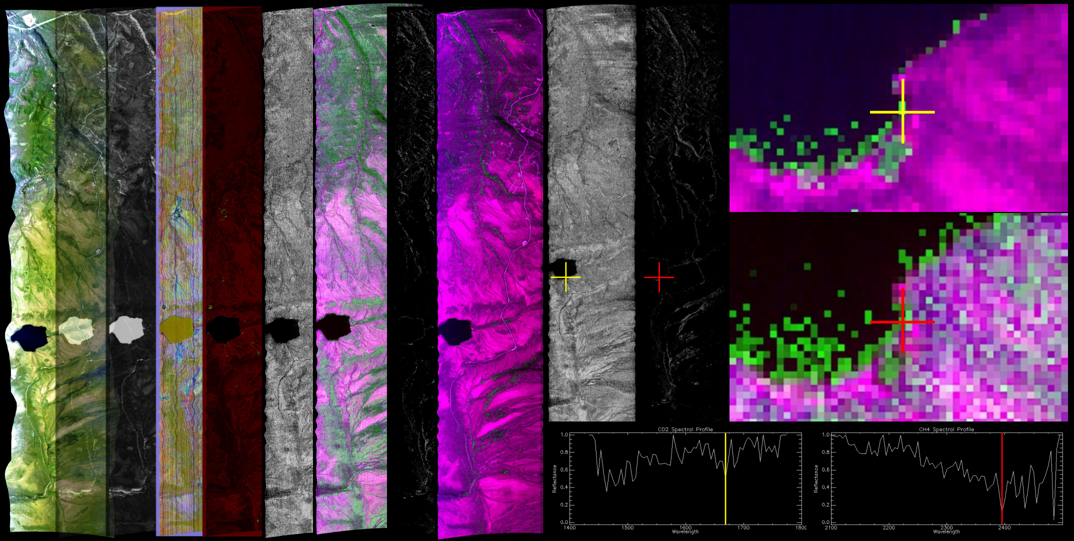
Data Dichotomy

What are the different modalities?

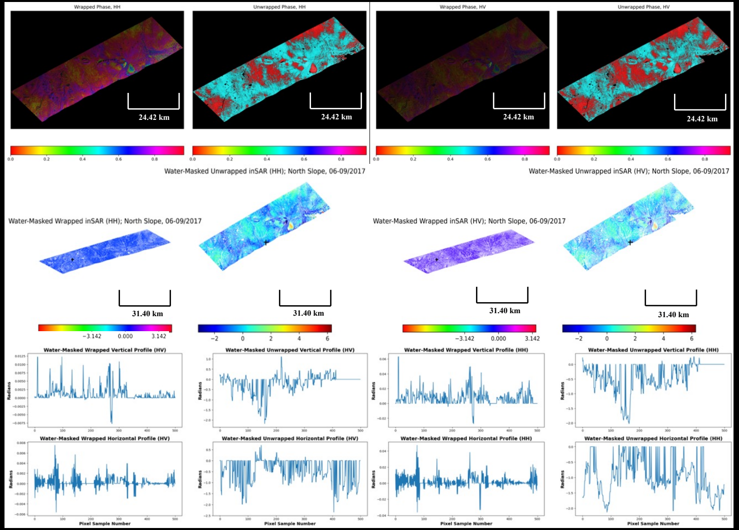
AVIRIS
Airborne Visible / Infrared Imaging Spectrometer

UAVSAR
NASA JPL AFRC





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



Eight Mile Lake, Denali North UAVSAR (L-band, polSAR RPI/inSAR VV/VV), 2017 July-September ∆) 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)

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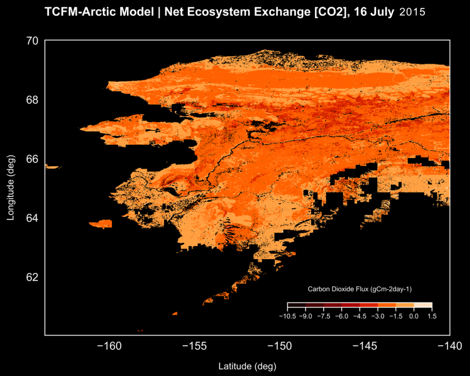
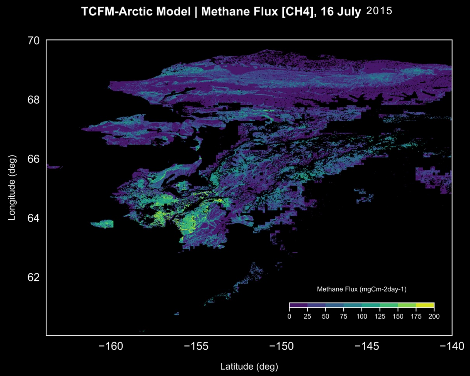
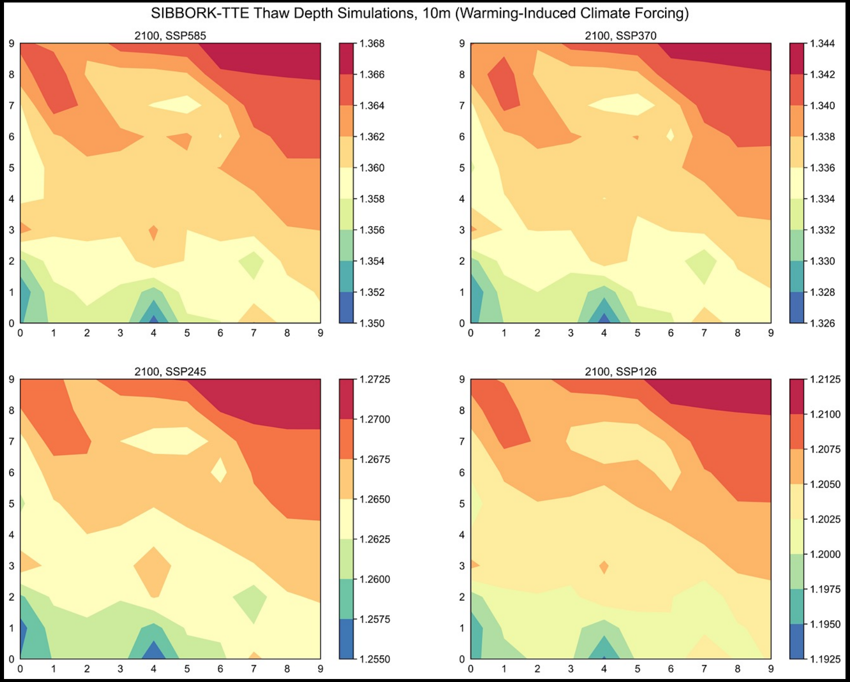
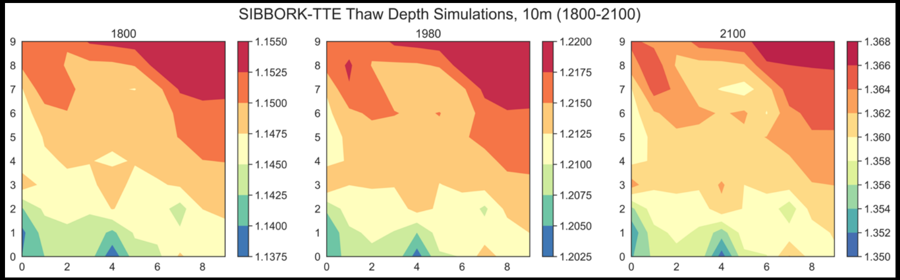
Data Dichotomy

What are the different modalities?









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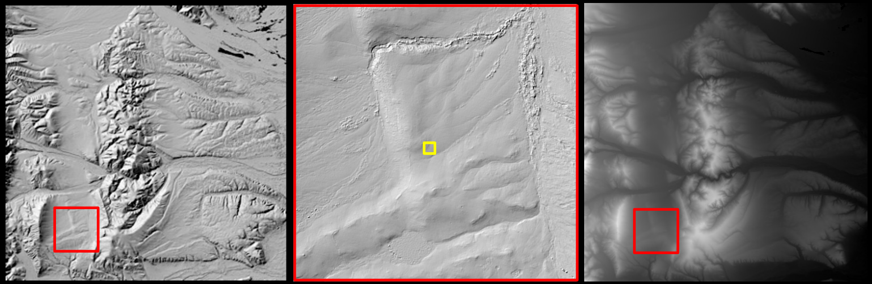
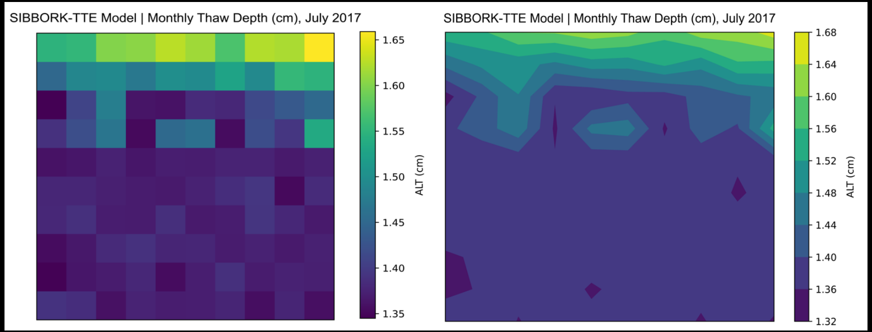
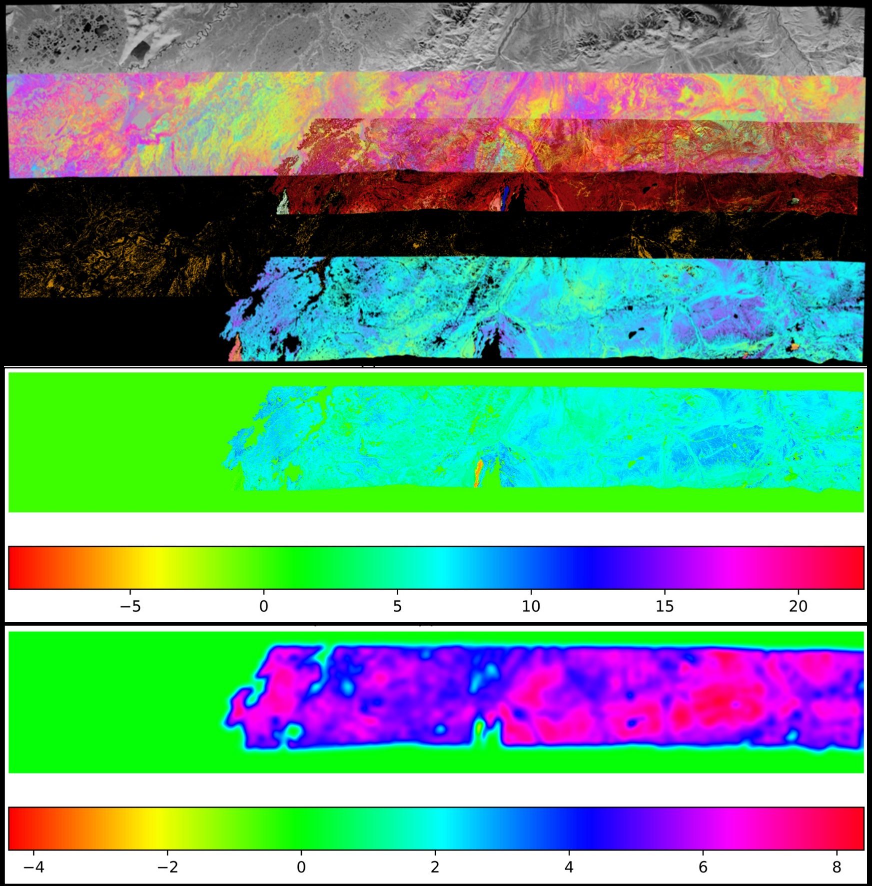
How is scale reconciled?

Spatial Disaggregation







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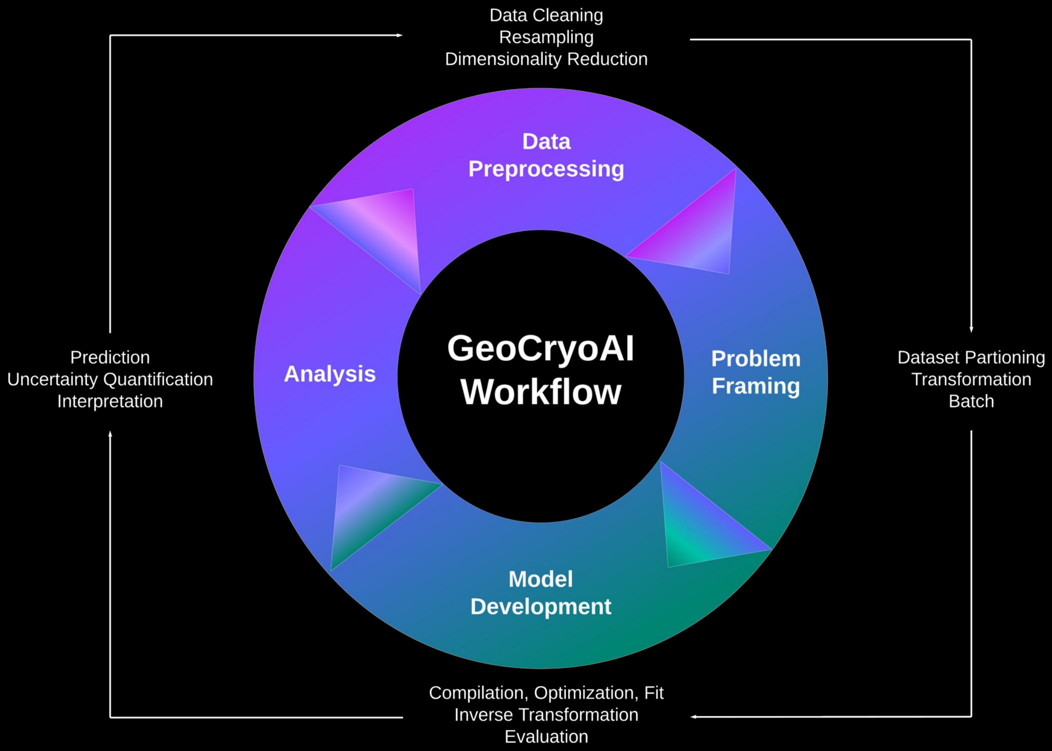
GeoCryoAI



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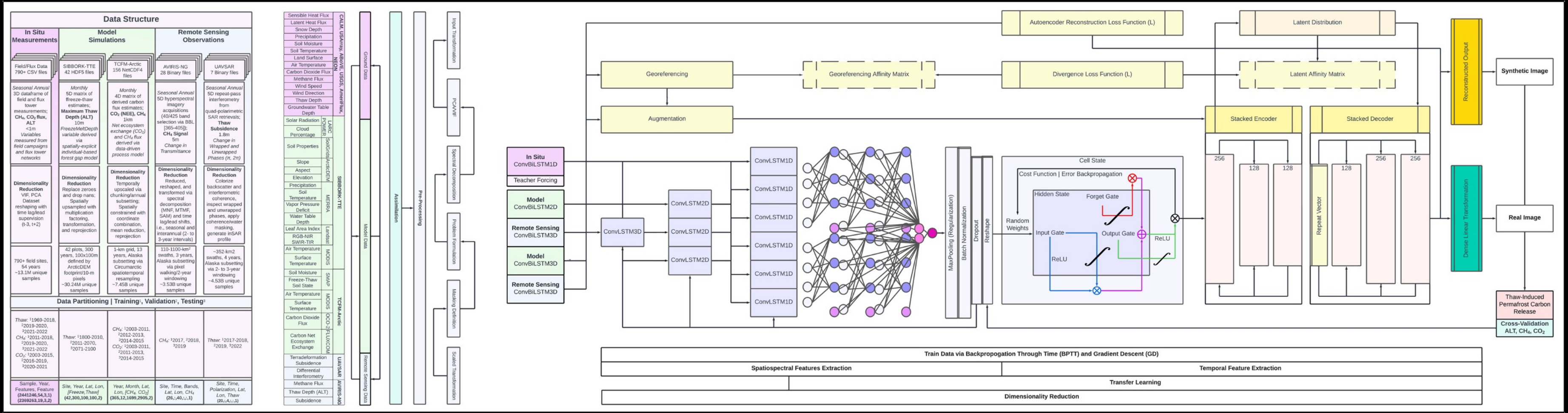
GeoCryoAI

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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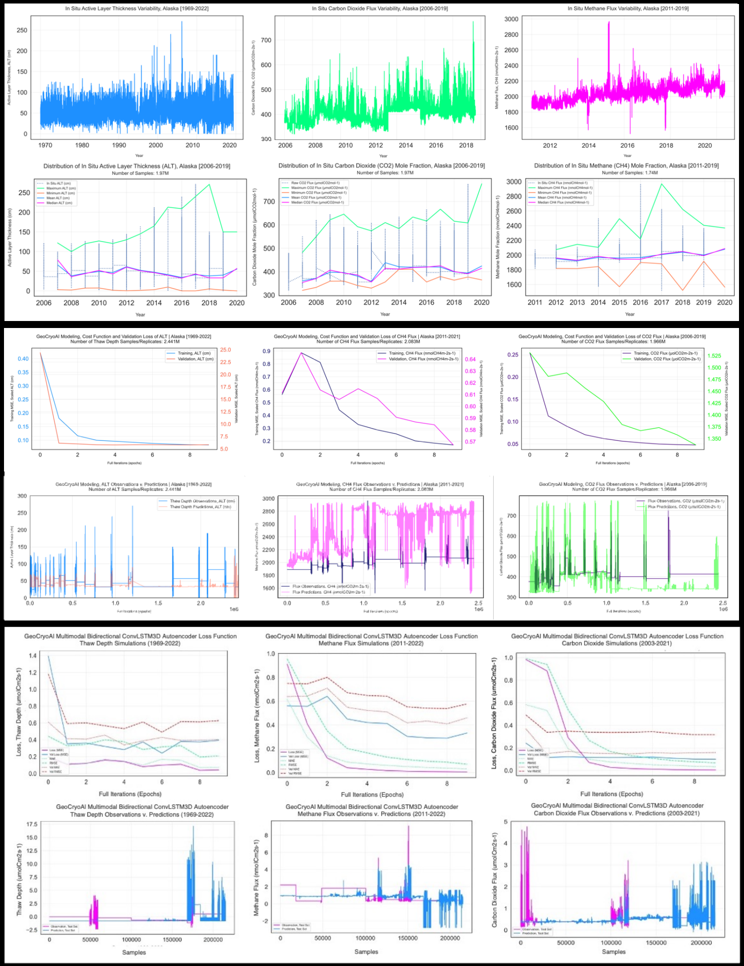
Results

Cost Functions and Performance



Time series analyses of ALT, CO_2, and CH_4 *in situ* measurements constrained to the temporal coverage of CO_2 and CH_4 flux variability across Alaska, 2006-2019 (**top**). Loss functions and predictions derived from GeoCryoAI simulations of *in situ* thaw depth and carbon release during teacher forcing (**middle**) and multimodal thaw depth and carbon release data (**bottom**).

	Active Layer Thickness (cm), 1969-2022	**Carbon Dioxide** ($\mu molCO_2m^{-2}s^{-1}$), 2003-2021	**Methane** ($nmolCH_4m^{-2}s^{-1}$), 2011-2022
Naïve Persistence Model			
Test RMSE	1.997	1.906	0.884
GeoCryoAI I Teacher Forcing			
Test RMSE	1.327	0.697	0.715
Fractional Reduction RMSE	-33.55%	-63.43%	-19.12%
GeoCryoAI I Multimodality			
Test MAE	0.708	0.09	0.591
Test MSE	1.014	0.045	0.481
Test MAPE	0.578	0.156	0.51
Test RMSE	1.007	0.213	0.694
Fractional Reduction RMSE	-49.57%, -24.11%	-88.82%,-69.44%	-21.49%, -2.94%

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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 provide a novel multidisciplinary approach to better understanding the Arctic ecosystem by constraining spatiotemporal complexities and refining traditional model parameterization efficiencies with state-of-the-art developments in HPC and AI.

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).
- 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 huge 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 recently (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 the PCF 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:

- **Enrichment** | Expanding the flexibility, efficiency, and knowledge base of the model with supercomputing and AI in support of current and future missions to minimize loss and improve performance (e.g., AVIRIS-3, UAVSAR, PREFIRE, NISAR, CRISTAL; SBG TIR)

- **Development** | Generating Circumarctic zero-curtain space-time maps to distribute to the State of Alaska, First Nations, and the USG 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 artificial intelligence (AI) tools and information derived from field-scale surveys across the tundra and boreal landscapes in Alaska. We identify and interpret the permafrost carbon cycling links and feedback sensitivities with GeoCryoAI, a hybridized multimodal deep learning (DL) architecture of stacked convolutionally layered, memory-encoded recurrent neural networks (NN). This framework integrates *in-situ* measurements and flux tower observations for teacher forcing and model training. Preliminary experiments to quantify, validate, and forecast permafrost degradation and carbon efflux across Alaska demonstrate the fidelity of this data-driven architecture. More specifically, GeoCryoAI logs the ecological memory and effectively learns covariate dynamics while demonstrating an aptitude to simulate and forecast PCF dynamics—active layer thickness (ALT), carbon dioxide flux (CO_2), and methane flux (CH_4)—with high precision and minimal loss (i.e. ALT^{RMSE}: 1.327 cm [1969–2022]; CO_2^{RMSE}: 0.697 $\mu molCO_2 m^{-2} s^{-1}$ [2003–2021]; CH_4^{RMSE}: 0.715 $nmolCH_4\, m^{-2} s^{-1}$ [2011–2022]). ALT variability is a sensitive harbinger of change, a unique signal characterizing the PCF, and our model is the first characterization of these dynamics across space and time.

1. Introduction

1.1. Permafrost carbon feedback

Frozen soil and carbon-rich permafrost characterizes nearly 14 million square kilometers of the global terrestrial surface, with total soil organic carbon stock estimates near 1307 ± 170 PgC (Hugelius *et al* 2014). Across the Circumarctic, quantifying the persistent irregularities and impacts attributed to permafrost degradation remains a scientific challenge. The transitional state of permafrost and spatiotemporal ALT heterogeneity drives abrupt changes emerging from rapid, nonlinear carbon-climate feedback mechanisms. These processes are correlated with several biotic and abiotic factors throughout the tundra and boreal, including tundra shrub encroachment, boreal forest migration, caribou migration patterns, topography, precipitation, solar radiation, land surface temperature, and subsurface hydrologic flow (Lloyd *et al* 2003, Evans *et al* 2020, Aguirre *et al* 2021, Joly *et al* 2021). Carbon release originating from the permafrost-carbon feedback is a climate change catalyst that amplifies localized warming patterns, disrupts carbon cycle partitioning, and destabilizes

Forecasting Permafrost Carbon Dynamics in Alaska with GeoCryoAI

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Key Points:

- We quantify and forecast the permafrost carbon feedback and reconcile the multimodal data dichotomy with artificial intelligence (GeoCryoAI).
- GeoCryoAI is a hybridized ensemble learning framework composed of stacked convolutional layers and memory-encoded recurrent neural networks.
- This approach provides refinements to traditional model inefficiencies and resolves spatiotemporal disparities in permafrost research.

Index Terms:

0702 Permafrost (0475, 4308)
0428 Carbon cycling (4806)
0758 Remote sensing
1910 Data assimilation, integration and fusion
1952 Modeling (0466, 0545, 0798, 1847, 4255, 4316)

Keywords:

permafrost carbon feedback, cryosphere, artificial intelligence, remote sensing, climate change, Alaska

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