European Polar Science Week

Parallel Session 19

The ESA-NASA Arctic Methane Permafrost Challenge (AMPAC) - Moving to the Future

Reconciling permafrost carbon dynamics, high-latitude thermal inertia, and the data dichotomy paradigm by leveraging artificial intelligence and multimodal data products

Bradley A. Gay

Jet Propulsion Laboratory | California Institute of Technology

5 September 2024

Jet Propulsion Laboratory
California Institute of Technology

GeoCryoAI

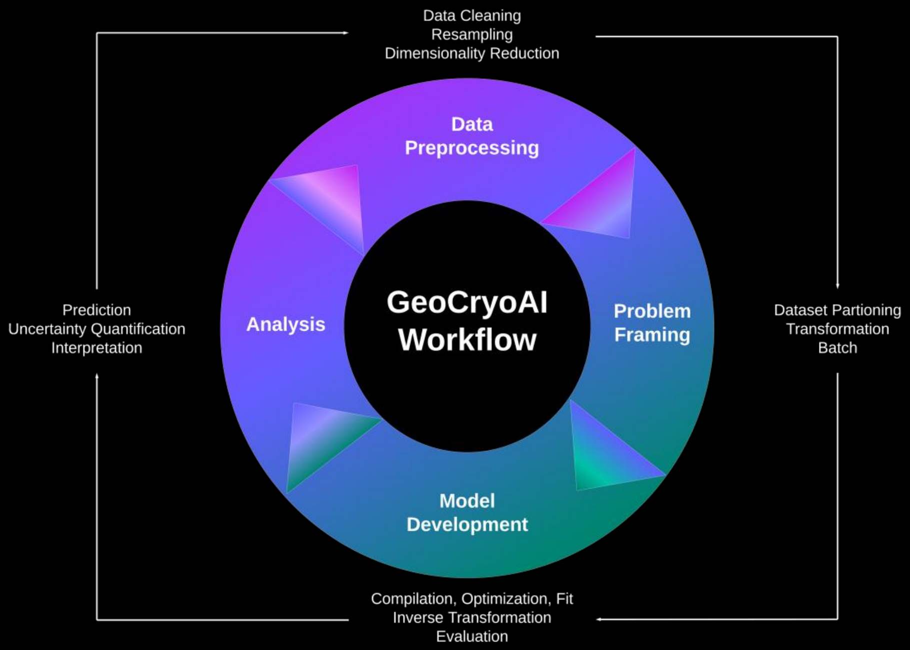
Summary of research and what application was investigated?

Problem

Reconciliation of Data Dichotomy with Artificial Intelligence

Application

Permafrost Carbon Feedback



Gay et al., 2023

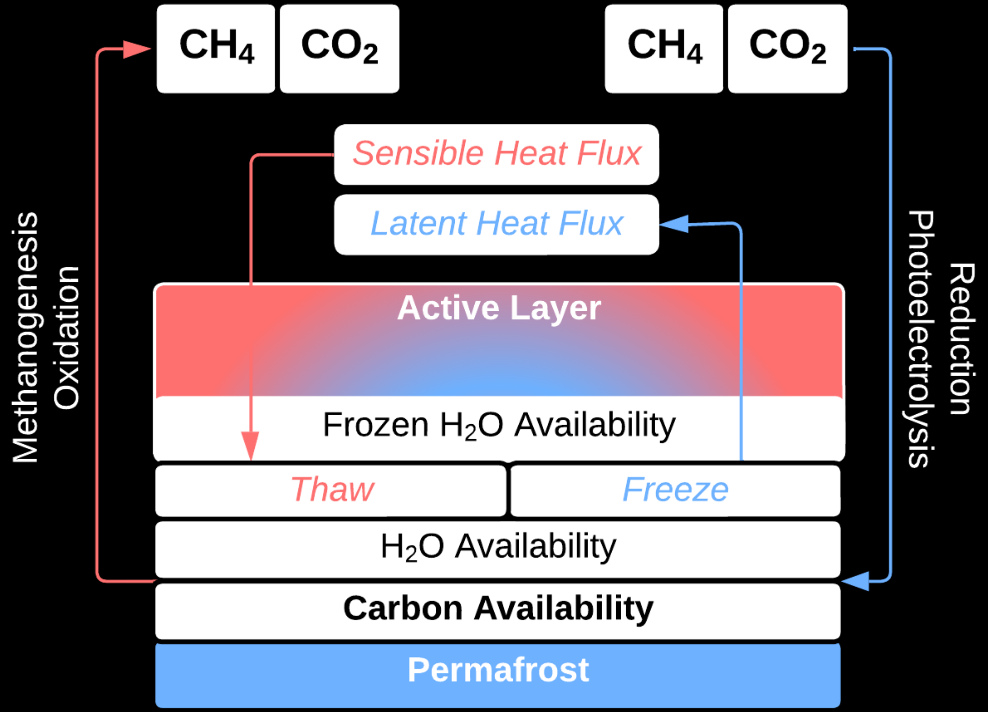
Gay et al., 2024. *Under Review*

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).



Gay et al., 2024. *Under Review*

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., scarcity 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).

Gay et al., 2024. *Under Review*

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 with reduced error.

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

Gay et al., 2023

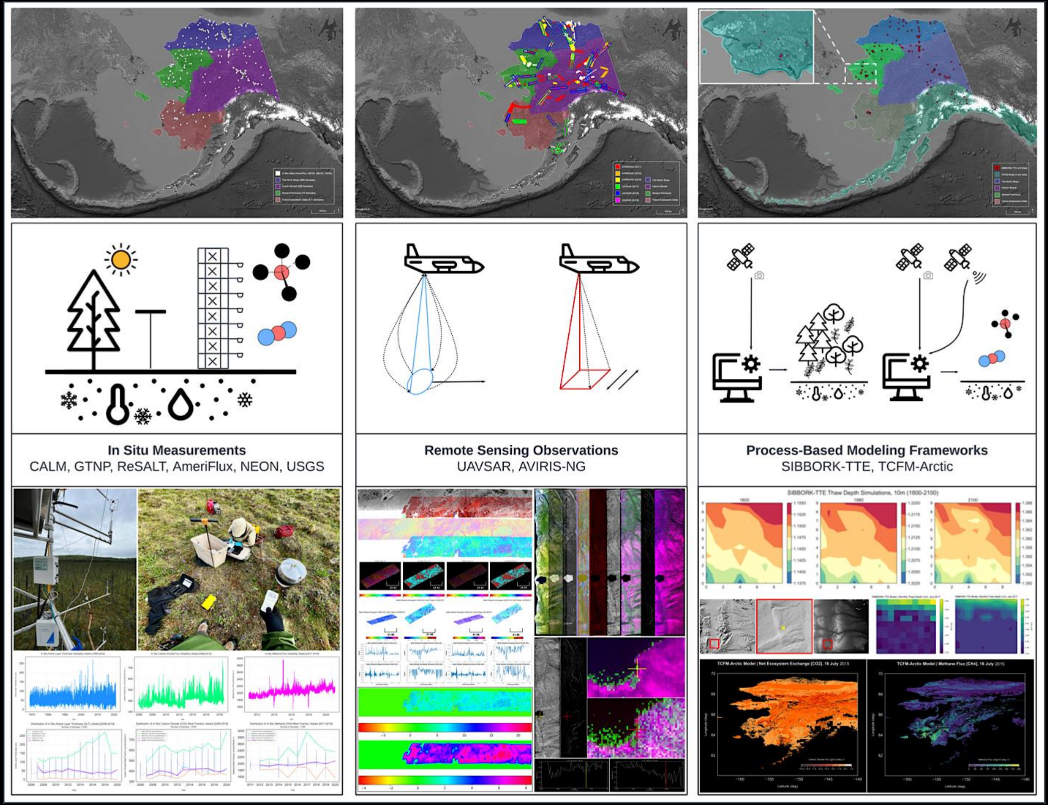
Gay et al., 2024. *Under Review*

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 12.1M parameters and high dimensional, time-variant multimodal hyperspatiospectral datasets:

- 2.96M *in situ* measurements (1030 field sites)
- 4.29B airborne observations (693 flight lines)
- 4.65B process-based model outputs



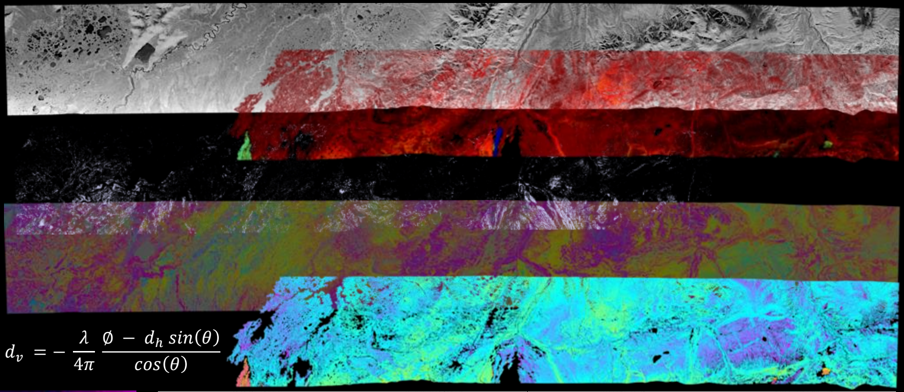
Gay et al., 2023

Gay et al., 2024. *Under Review*

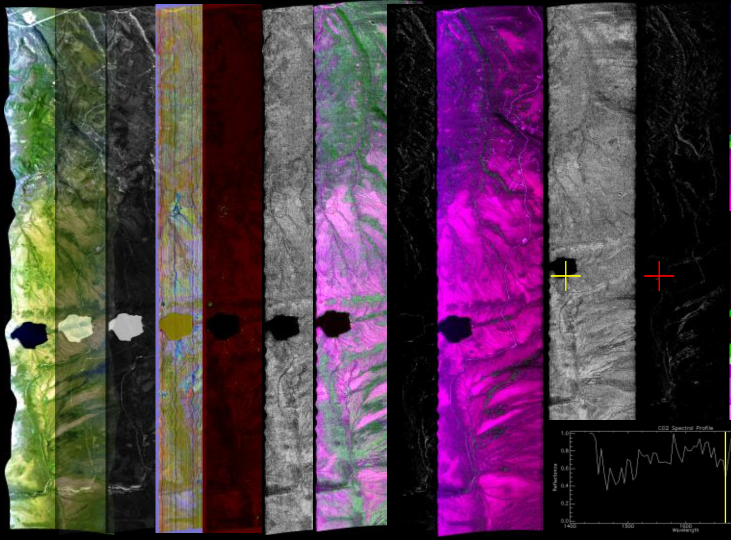
Data Dichotomy

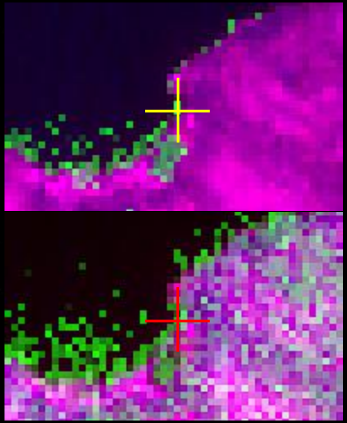
What are the different modalities?

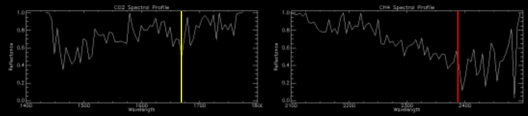
Airborne Visible / Infrared Imaging Spectrometer

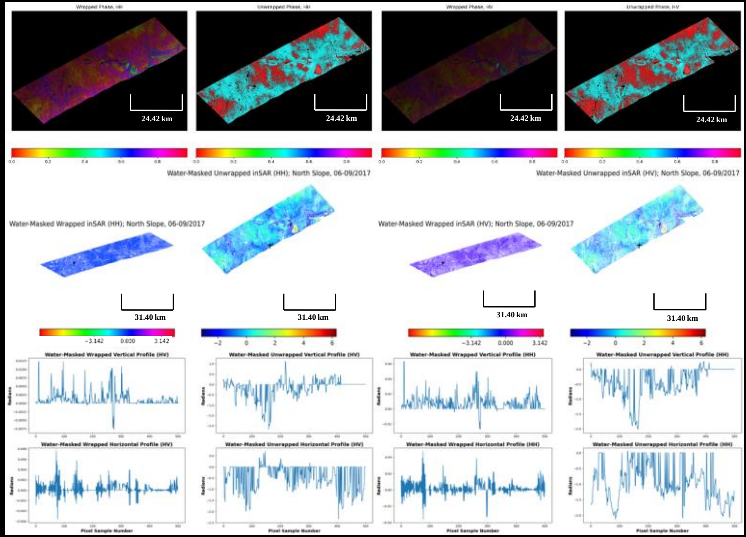


$$d_v = -\frac{\lambda}{4\pi}\,\frac{\emptyset - d_h \sin(\theta)}{\cos(\theta)}$$









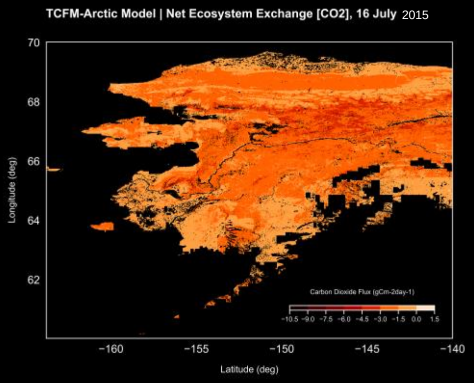
Gay et al., 2024. *Under Review*

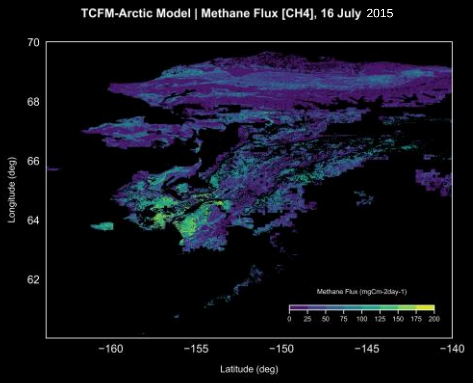
Eight Mile Lake AVng_242A-242Z_FL194 AVIRIS-NG: (RGB; 44.914 km), ang20170706t183519_rdn_v2p9

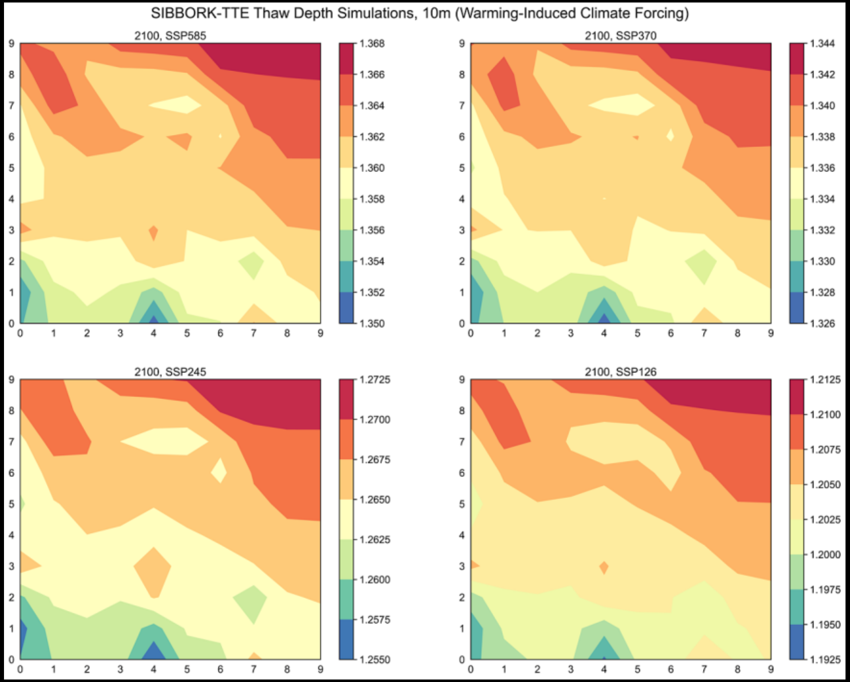
Eight Mile Lake, Denali North UAVSAR (L-band, polSAR RPI/inSAR VV/VV), 2017 July-September ∆) denalN_09115_17066-008_17100-003_0094d_s01_L090_01; 29396, 4811, 4.99m, 17-Jun-2017 22:29:35-22:41:16 UTC-19-Sep-2017 21:30:17-21:41:14 UTC, 160-km length of processing data (Linear Power, Phase Radians)

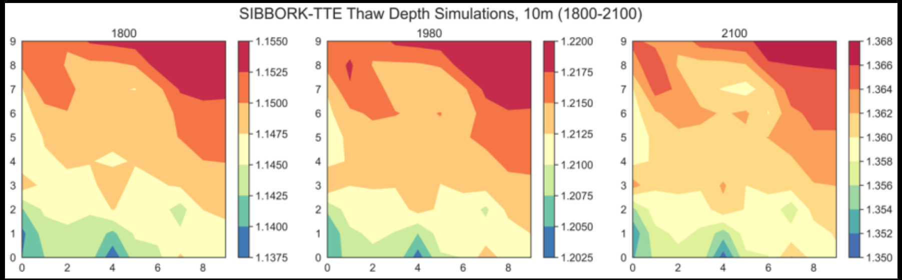
Data Dichotomy

What are the different modalities?





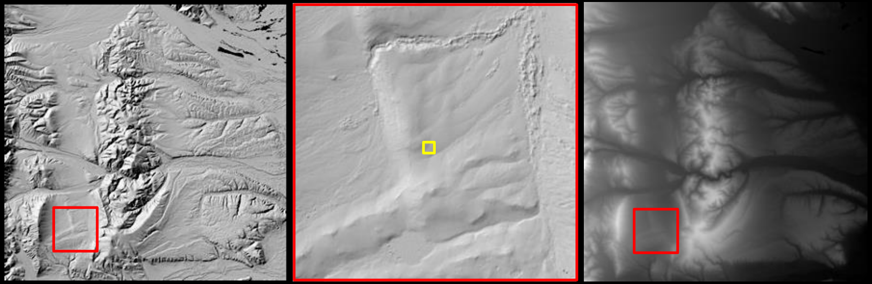


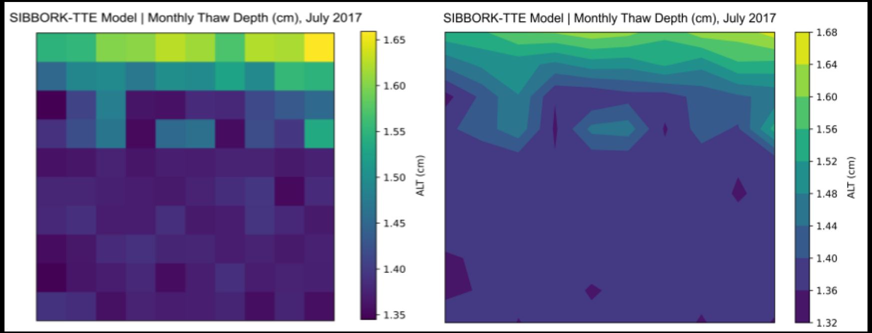


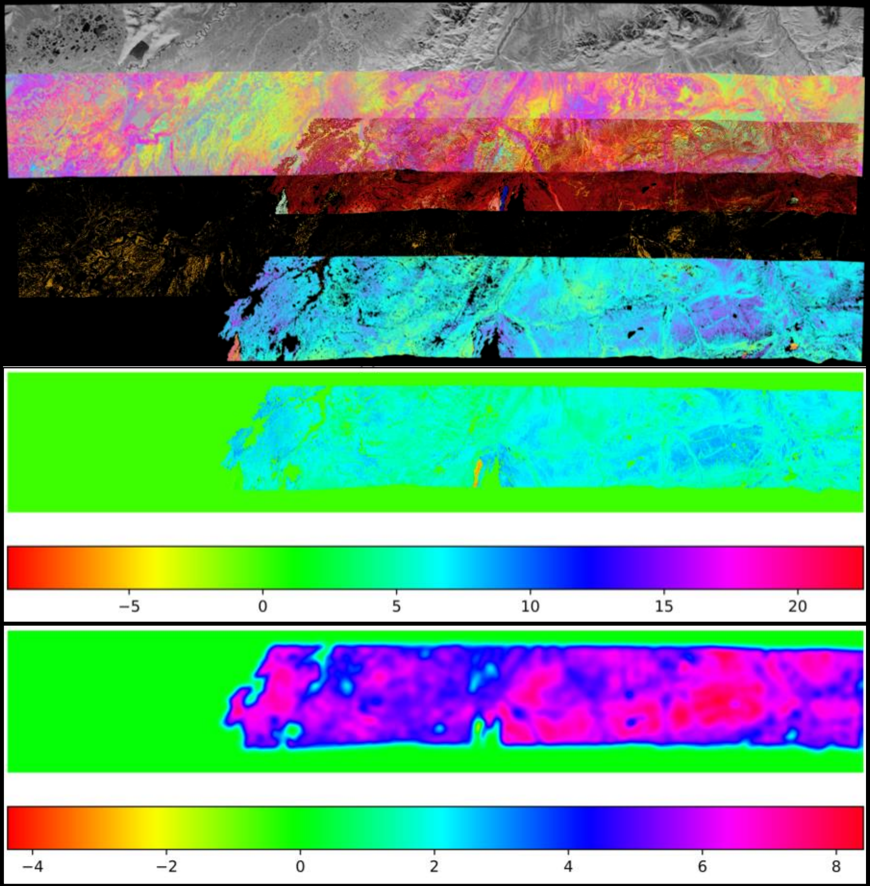
Gay et al., 2024. *Under Review*

How is scale reconciled?

Spatial Disaggregation

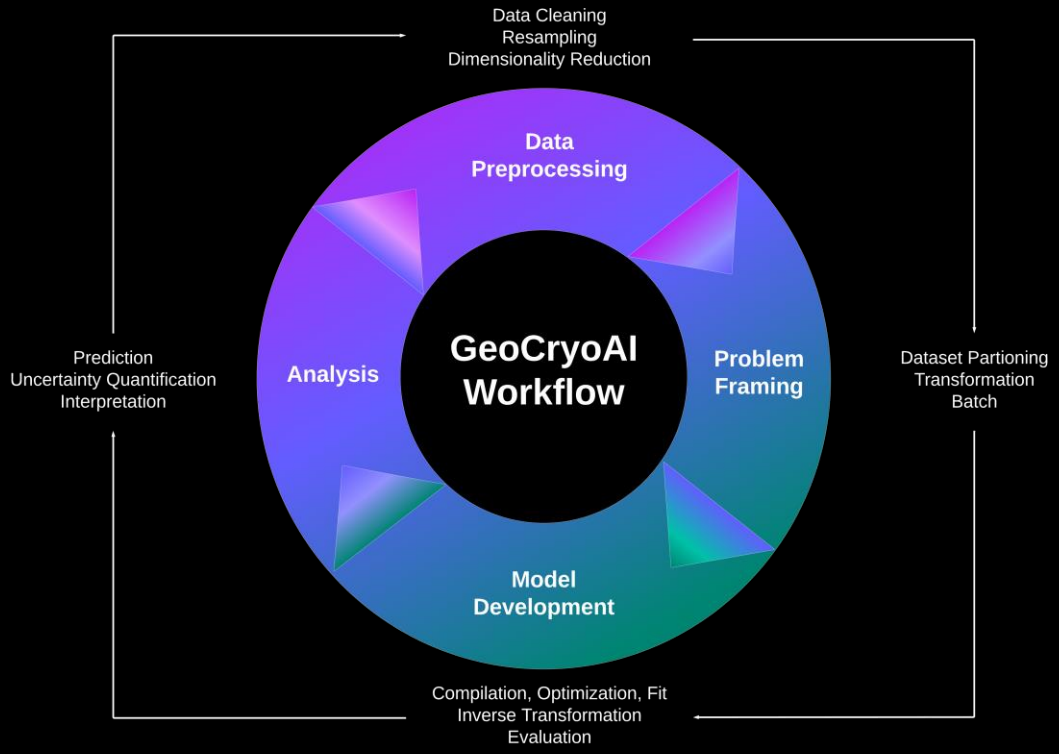






Gay et al., 2024. *Under Review*

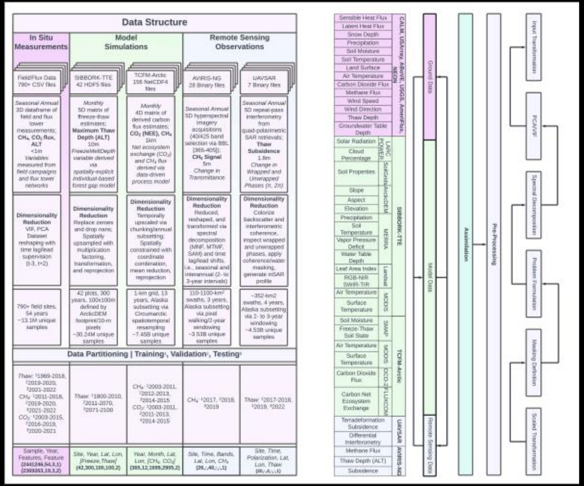
GeoCryoAI

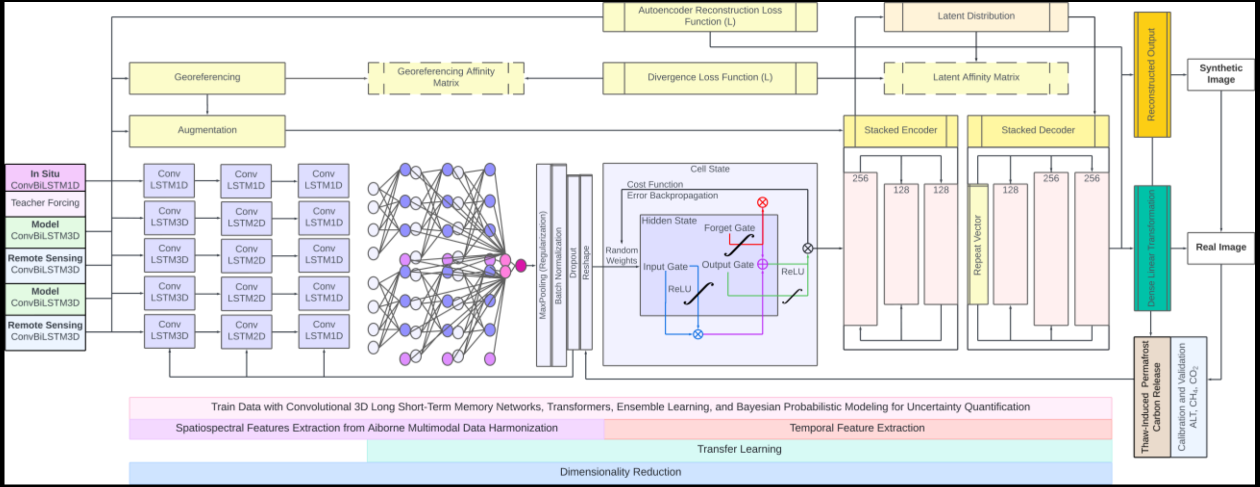


Gay et al., 2023

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.

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

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

Gay et al., 2023

Gay et al., 2024. *Under Review*

Results

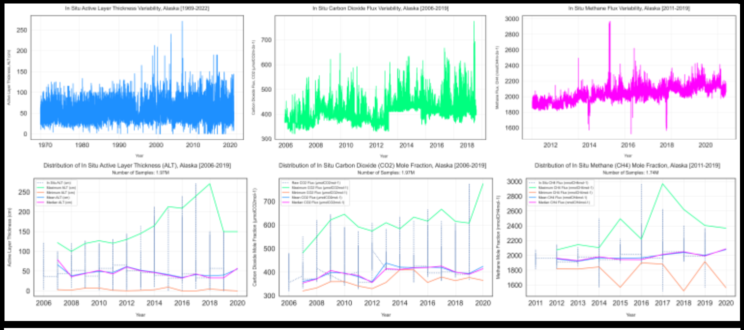
Cost Functions and Performance

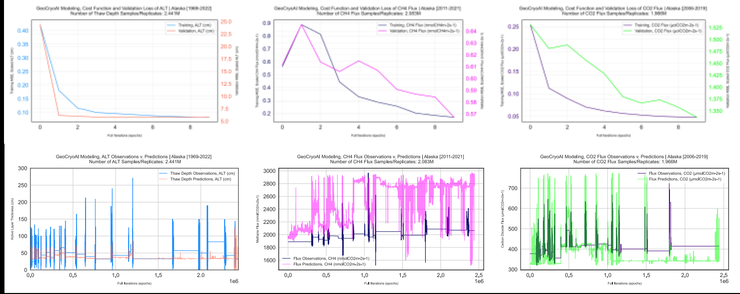
Time series analyses of ALT, CO_2, and CH_4 *in situ* measurements constrained to the temporal coverage of CO_2 and CH_4 flux variability across Alaska, 2006-2019 (**top**). Loss functions and predictions derived from GeoCryoAI simulations of *in situ* thaw depth and carbon release during teacher forcing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

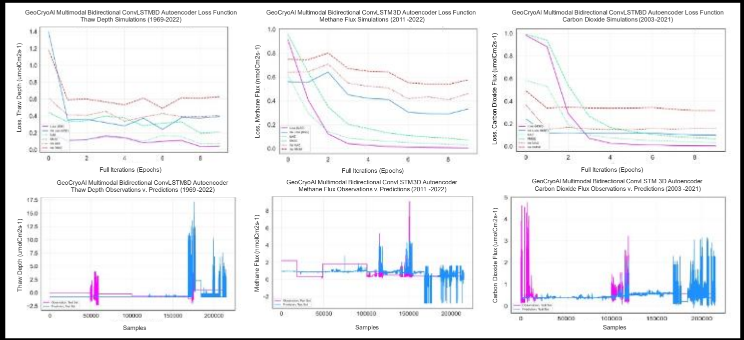
	Active Layer Thickness $\frac{\delta}{\delta_z}$cm, 1800-2100	**Carbon Dioxide** $\mu molCO_2mol^{-1}km^{-2}month^{-1}$ 1996-2022	**Methane** $nmolCH_4mol^{-1}km^{-2}month^{-1}$ 1996-2022
Naïve Persistence			
Test RMSE	**1.997**	**1.906**	**0.884**
GeoCryoAI Teacher Forcing			
Test RMSE	1.327	0.697	0.715
Frac. Reduction RMSE	-33.55%	-63.43%	-19.12%
GeoCryoAI 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**
Frac. Reduction RMSE	-49.57%, -24.11%	-88.82%,-69.44%	-21.49%, -2.94%

Gay et al., 2023

Gay et al., 2024. *Under Review*







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*. Like previous studies, we found the performance of DL algorithms and ensemble predictions to outperform traditional regression methods when estimating GHG fluxes (Virkkala et al., 2021).
- The model's ability to harmonize multimodal data enhances the accuracy of subsurface monitoring and provides more reliable estimates of ALT and permafrost state. Additionally, we address the need to better understand *how* and *to what extent* thawing permafrost destabilizes the carbon balance in Alaska by integrating a novel multidisciplinary approach and framework that constrains spatiotemporal complexities, simulates nonlinear interactions among PCF covariates, refines traditional model parameterizations, and affords the flexibility to ingest and assimilate multimodal data to simulate rapid and stochastic thaw events.

Limitations

- Though validation and testing loss improved for CH_4, forecasting the CH_4 signal variability was challenging during teacher forcing (i.e., failed to stabilize during abrupt change in the CH_4 signal and consistently overestimated CH_4 flux). By introducing more data into the framework, this discrepancy was ameliorated with limited validation and testing loss changes. However, new challenges emerged, and the model failed to capture and predict initial pulses of thaw subsidence and CO_2 release.
- 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. In addition, 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 *uncertainties* may originate from landscape-level dynamics and regional lagged effects in response to increased warming.

Gay et al., 2024. *Under Review*

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.

Gay et al., 2024. *Under Review*

Ongoing Research and Steps Forward

What is next?

Takeaway: Artificial intelligence is *inherently* biased by current human understanding of complex systems. However, it is a *valuable* tool for developing climate change mitigation strategies, infrastructure security, and global, federal, state, and local policymaking. 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 |** Resolving the zero-curtain effect with subsurface thermal gradients and freeze-thaw transitions and generating Circumarctic zero-curtain space-time maps using radar polarimetry, thermal imaging, and quantum AI technology to distribute to the State of Alaska, First Nations, 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)

Gay et al., 2024. *Under Review*

Acknowledgements

References

Barrett, B.W., et al. (2009). https://doi.org/10.3390/rs1030210
Beamish, A., et al. (2020). https://doi.org/10.1016/j.rse.2020.111872
Bruhwiler, L., et al. (2021). https://doi.org/10.1007/s40641-020-00169-5
Cusworth, D.H., et al. (2020). https://doi.org/10.1029/2020gl087869
Dubovik, O., et al. (2021). https://www.frontiersin.org/articles/10.3389/frsen.2021.619818
Elder, C.D., et al. (2021). https://doi.org/10.1029/2020gb006922
Foote, M.D., et al. (2020). https://doi.org/10.1109/TGRS.2020.2976888
Foote, M.D., et al. (2021). https://doi.org/10.1016/j.rse.2021.112574
Frankenberg, C., et al. (2016). https://doi.org/ 10.1073/pnas.1605617113
Gay, B.A., et al. (2024). *Under Review*.
Gay, B.A., et al. (2023). https://doi.org/10.1088/1748-9326/ad060
Gay, B.A., et al. (2022). https://doi.org/10.22541/essoar.167252578.88217202/v1
Gay, B.A., et al. (2022). https://doi.org/10.1002/essoar.10509696.1
Gay, B.A., et al. (2021). https://doi.org/10.1002/essoar.10505831.1
He, K., et al (2018). https://doi.org/10.48550/arXiv.1703.06870
Hinkel, K.M., Nelson, F.E. (2003). https://doi.org/10.1029/2001JD000927
Hjort J, et al. (2018). https://doi.org/10.1038/s41467-018-07557-4
Hu, G., et al. (2017). https://doi.org/10.1007/s00703-016-0468-7
Jiang, H., et al. (2020). https://www.frontiersin.org/articles/10.3389/feart.2020.560403
Kochanov, R.V., et al. (2016). https://doi.org/10.1016/j.jqsrt.2016.03.00
Kokaly, R.F., et al. (2017). https://doi.org/10.3133/ds1035
Li, X., et al. (2014). https://doi.org/10.48550/arxiv.1410.4281
Lloyd, A., et al. (2003). https://doi.org/10.1002/ppp.446
Peterson, G. (2002). https://doi.org/10.1007/s10021-001-0077-1
Raynolds, M.A., et al. (2006). https://doi.org/10.1127/0340-269X/2005/0035-0821
Raynolds, M.K., et al. (2019). https://doi.org/10.1016/j.rse.2019.111297
Roger, J., et al. (2023). https://doi.org/10.5194/amt-2023-168
Sak, H., et al. (2014). https://doi.org/10.48550/arXiv.1402.1128
Scafutto, R.D.P.M., et al. (2021). https://doi.org/10.1016/j.jag.2020.102233
Schmugge, T., et al. (1992). https://doi.org/10.1016/0924-2716(92)90029-9
Sepp Hochreiter, et al. (1997). https://doi.org/10.1162/neco.1997.9.8.1735
Shugart, H.H., et al. (1980). https://doi.org/10.2307/1307854
Shugart, H.H., et al. (2018). https://doi.org/10.1088/1748-9326/aaaacc
Theiler, J. (2012). https://doi.org/10.1117/12.918718
Thompson, D.R., et al. (2015). https://doi.org/10.5194/amt-8-4383-2015
Thompson, D.R., et al. (2015). https://doi.org/10.1016/j.rse.2015.02.010
Thorpe, A.K., et al. (2014). https://doi.org/10.5194/amt-7-491-2014
Thorpe, A.K., et al. (2017). https://doi.org/10.5194/amt-10-3833-2017
Thorpe, A.K., et al. (2013). https://doi.org/10.1016/j.rse.2013.03.018
Watts, J., et al. (2023). https://doi.org/10.1111/gcb.16553
Xingjian, S., et al. (2015). https://doi.org/10.48550/arXiv.1506.04214
You, J., et al. (2017). https://doi.org/10.1609/aaai.v31i1.11172

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

IOP Publishing Environ. Res. Lett. **18** (2023) 125001 https://doi.org/10.1088/1748-9326/ad0607

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
22 February 2023

REVISED
10 October 2023

ACCEPTED FOR PUBLICATION
23 October 2023

PUBLISHED
16 November 2023

LETTER

Investigating permafrost carbon dynamics in Alaska with artificial intelligence

B A Gay[1,2,*], N J Pastick[3], A E Züfle[1,4], A H Armstrong[5], K R Miner[2] and J J Qu[1]

1 George Mason University, Department of Geography and Geoinformation Science, Fairfax, VA, United States of America
2 NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, United States of America
3 United States Geological Survey, Earth Resources Observation and Science Center, Sioux Falls, SD, United States of America
4 Emory University, Department of Computer Science, Atlanta, GA, United States of America
5 University of Maryland, Earth System Science Interdisciplinary Center, College Park, MD, United States of America
* Author to whom any correspondence should be addressed.

E-mail: bradley.a.gay@jpl.nasa.gov

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

Manuscript Submitted to *Journal of Geophysical Research | Machine Learning and Computation*

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

B.A. Gay[1], N.J. Pastick[2], J.D. Watts[3,4], A.H. Armstrong[5], K.R. Miner[1], and C.E. Miller[1]

[1] Jet Propulsion Laboratory, California Institute of Technology. Pasadena, California USA.
[2] United States Geological Survey, Earth Resources Observation and Science Center. Sioux Falls, South Dakota USA.
[3] Montana State University, Bozeman, Montana USA.
[4] Woodwell Climate Research Center, Falmouth, Massachusetts USA.
[5] NASA Goddard Space Flight Center, Greenbelt, Maryland USA.
Corresponding author: Bradley Gay (bradley.a.gay@jpl.nasa.gov)

Key Points:

- We quantify nonlinear dynamics of the permafrost carbon feedback and reconcile the multimodal data dichotomy with artificial intelligence.
- GeoCryoAI is a hybridized ensemble learning architecture with stacked convolutional layers and memory-encoded recurrent neural networks.
- This optimized framework substantially improves the efficiency, scalability, and precision of simulating the permafrost carbon feedback.

Index Terms:

0702 Permafrost (0475, 4308)
0428 Carbon cycling (4806)
0758 Remote sensing
1952 Modeling (0466, 0545, 0798, 1847, 4255, 4316)
0555 Neural networks, fuzzy logic, machine learning (1942)

Keywords:

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

 1

Author Contact Information: bradley.a.gay@jpl.nasa.gov

Jet Propulsion Laboratory
California Institute of Technology