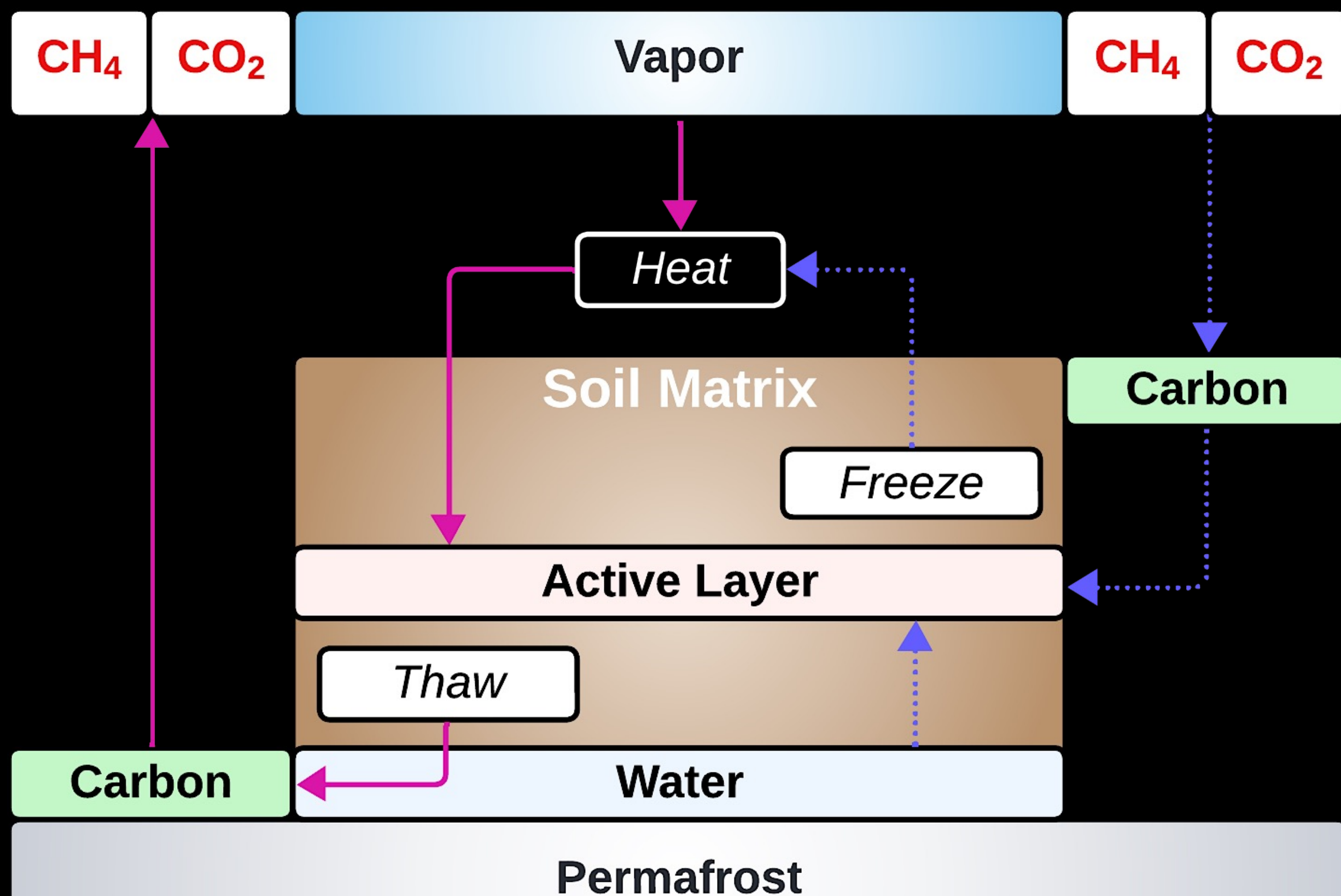


Investigating High-Latitude Permafrost Carbon Dynamics with Artificial Intelligence and Earth System Data Assimilation | Abstract ID: 1353228

Bradley A. Gay¹, Andreas E. Züfle², Amanda H. Armstrong³, Neal J. Pastick⁴, Jennifer D. Watts⁵, Paul A. Dirmeyer⁶, Kimberley R. Miner¹, Konrad J. Wessels⁶, John J. Qu⁶ and Charles E. Miller¹

(1) Jet Propulsion Laboratory, California Institute of Technology (2) Emory University (3) University of Maryland Earth System Science Interdisciplinary Center (4) United States Geological Survey, Earth Resources Observation Science Center (5) Woodwell Climate Research Center (6) George Mason University

BACKGROUND



Frozen soil and carbon-rich permafrost characterizes approximately 14 million square kilometers globally, with soil organic carbon stock estimated at 130 ± 170 PgC (Hugelius et al., 2014). *Thaw-induced carbon release is a climate change catalyst* and when coupled with anthropogenic-induced warming trigger, accelerate, and sustain a positive nonlinear carbon-climate feedback for hundreds of thousands of years (Schuur et al., 2015). The variability of thaw-induced carbon release and feedback mechanisms challenge efforts to quantify the magnitude, rate, and extent of the *permafrost carbon feedback* (PCF; Miner et al., 2021).

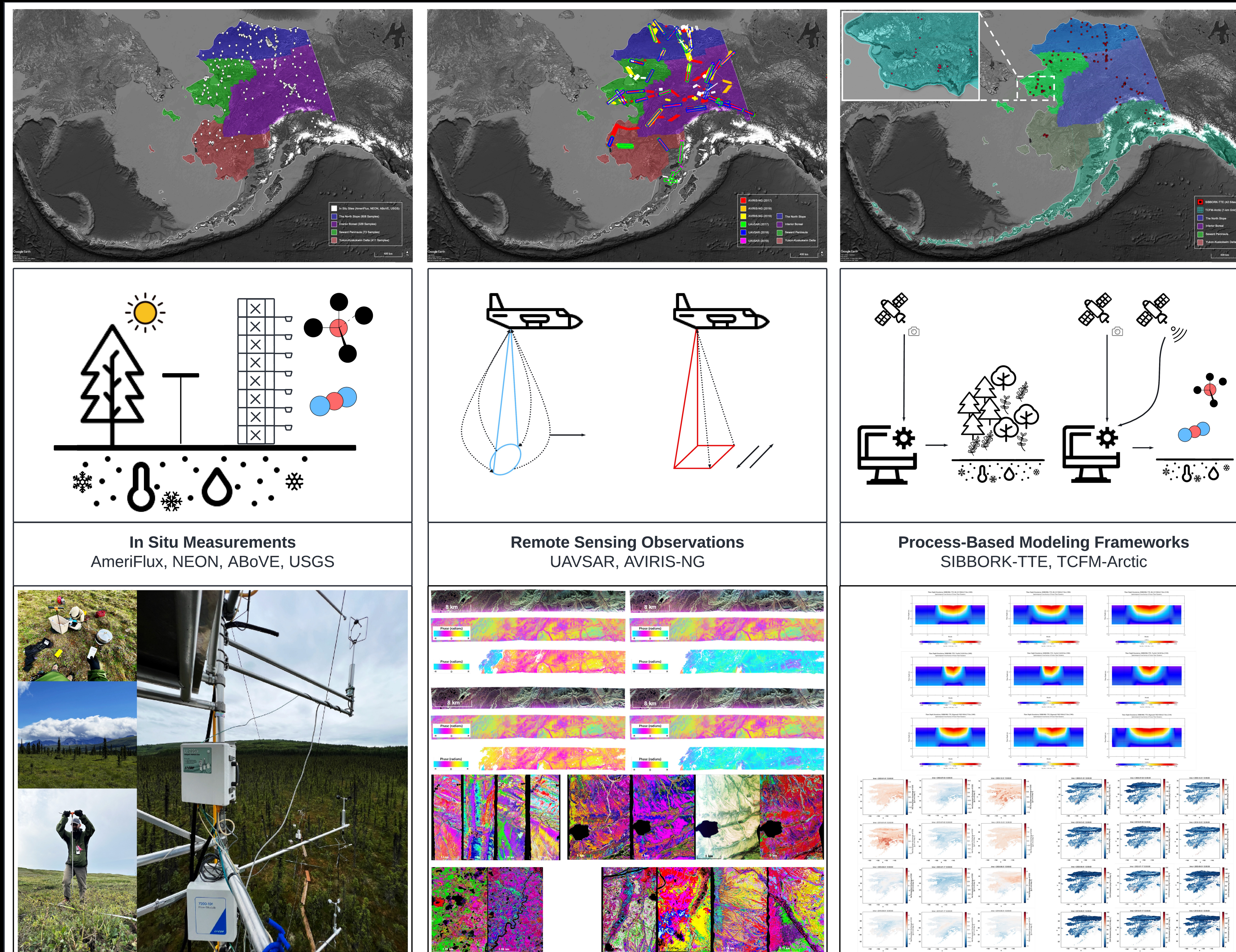
Due to spatiotemporal limitations, instrument constraints, and other challenges in the high latitudes (e.g., frequent cloud cover, short summer periods, low illumination angles), the ability to quantify or infer thaw variability with high confidence is restricted with remote sensing platforms (Gay, 2023; Esau et al., 2023). Moreover, subroutines and interactions governing earth system models vary widely, often overlooking the dynamics and long-term impacts of the PCF (Li et al., 2017; Randall 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 control factors contributing to the PCF signal* to better understand periglacial processes, carbon-climate interactions, biogeochemical relationships, and the hidden determinants of ecological memory in the high latitude earth system.

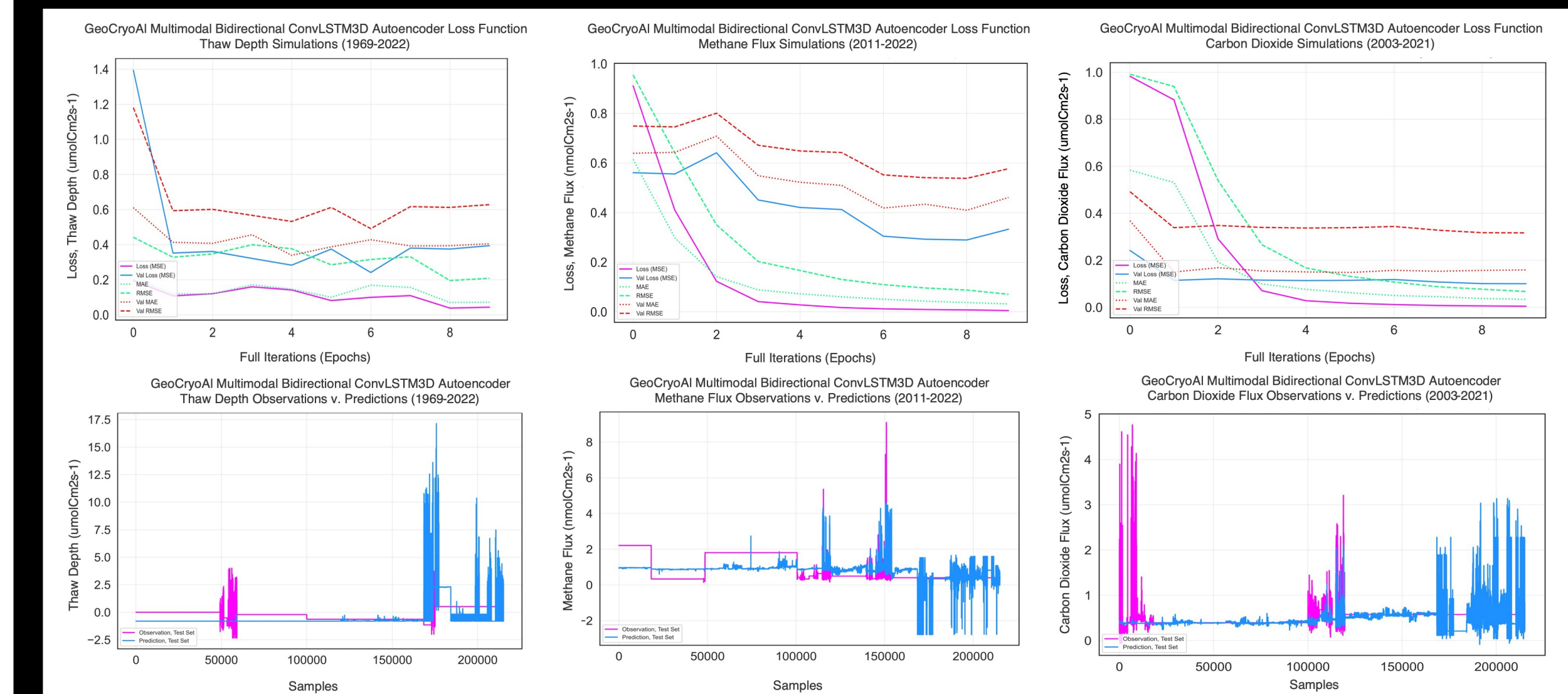


METHODS



RESULTS

Evaluation of time-delayed naïve persistence and GeoCryoAI simulations yielded the following error metrics (RMSE) with loss functions and predictions illustrated in the plots below: ALT: 1.997cm, 1.327cm [1969-2022]; CH₄: 0.884nmolCH₄m⁻²s⁻¹, 0.715nmolCH₄m⁻²s⁻¹ [2011-2022]; CO₂: 1.906μmolCO₂m⁻²s⁻¹, 0.697μmolCO₂m⁻²s⁻¹ [2006-2019].



SIGNIFICANCE AND FUTURE WORK

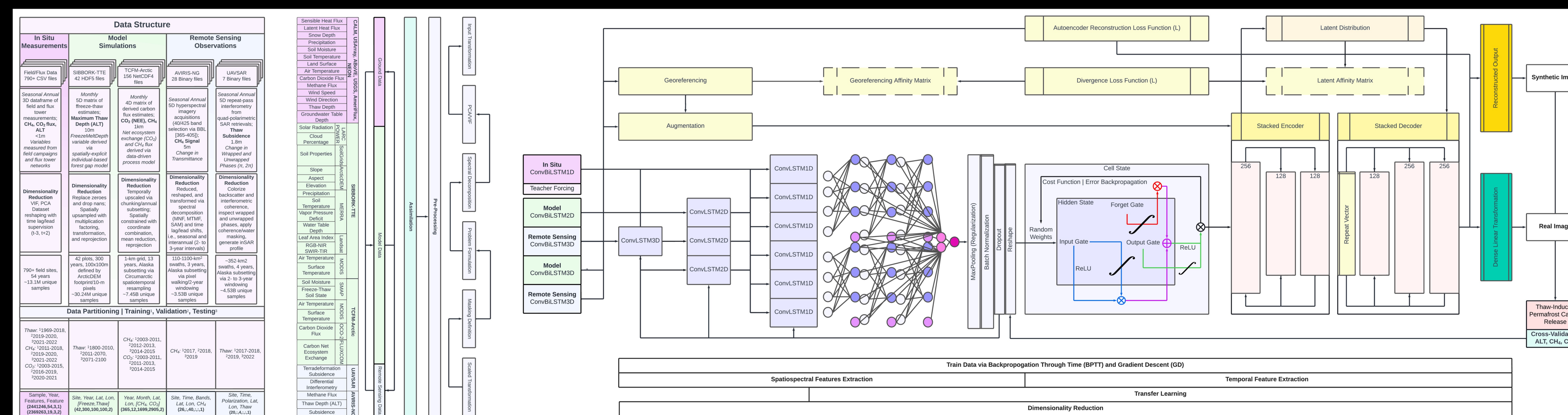


This study underscores the significance of thaw-induced climate change exacerbated by the PCF and highlights the importance of resolving the spatiotemporal variability of ALT as a sensitive harbinger of change. Ongoing research elucidates on the PCF and delayed subsurface phenomena by (1) *expanding the flexibility and knowledge base of the model with current and future missions to minimize loss and improve performance* (e.g., AVIRIS-3, UAVSAR, TROPOMI, PREFIRE, NISAR, CRISTAL; UAS DSMs; TIR), and (2) *generating Circumarctic zero-curtain space-time maps* to distribute to the State of AK, 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). Datasets, code, and notebooks are distributed in a [GitHub](#) repository.

PUBLICATIONS | ACKNOWLEDGEMENTS

- Gay, B.A., et al. (2023). Forecasting Permafrost Carbon Dynamics with Earth Observation Data and AI. Remote Sensing of Environment. *Under Review*.
- Gay, B.A., et al. (2023). Investigating Permafrost Carbon Dynamics in Alaska with Artificial Intelligence. Environmental Research Letters. doi.org/10.1088/1748-9326/ad0600
- Gay, B.A., et al. (2022). Quantifying Feedback Sensitivities of Permafrost Degradation and Carbon Release with Earth Observation Data and Feedback Neural Networks. Earth and Space Open Archive. doi.org/10.22541/essoar.167252578.88217202/v1
- Gay, B.A., Armstrong, A.H., Montesano, P.M., Osmanoglu, B., Ranson, K.J., and Epstein, H. (2022). Understanding Active Layer Thickness Variability Under Changing Climatic Conditions Across the North American Taiga-Tundra Ecotone. Earth and Space Science Open Archive. doi.org/10.1002/essoar.10509696.1
- Gay, B.A., Armstrong, A.H., Montesano, P.M., Osmanoglu, B., Ranson, K.J., and Epstein, H. (2021). Examination of Current and Future Permafrost Dynamics Across the North American Taiga-Tundra Ecotone. Earth and Space Science Open Archive. doi.org/10.1002/essoar.10505831.1

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



After transformation, dimensionality reduction, trend removal, time-delayed supervision, and regression analyses, model training initializes 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).