ARCTIC - BOREAL VULNERABILITY EXPERIMENT

Jet Propulsion Laboratory
California Institute of Technology

Forecasting Permafrost Carbon Dynamics in Alaska with GeoCryoAI

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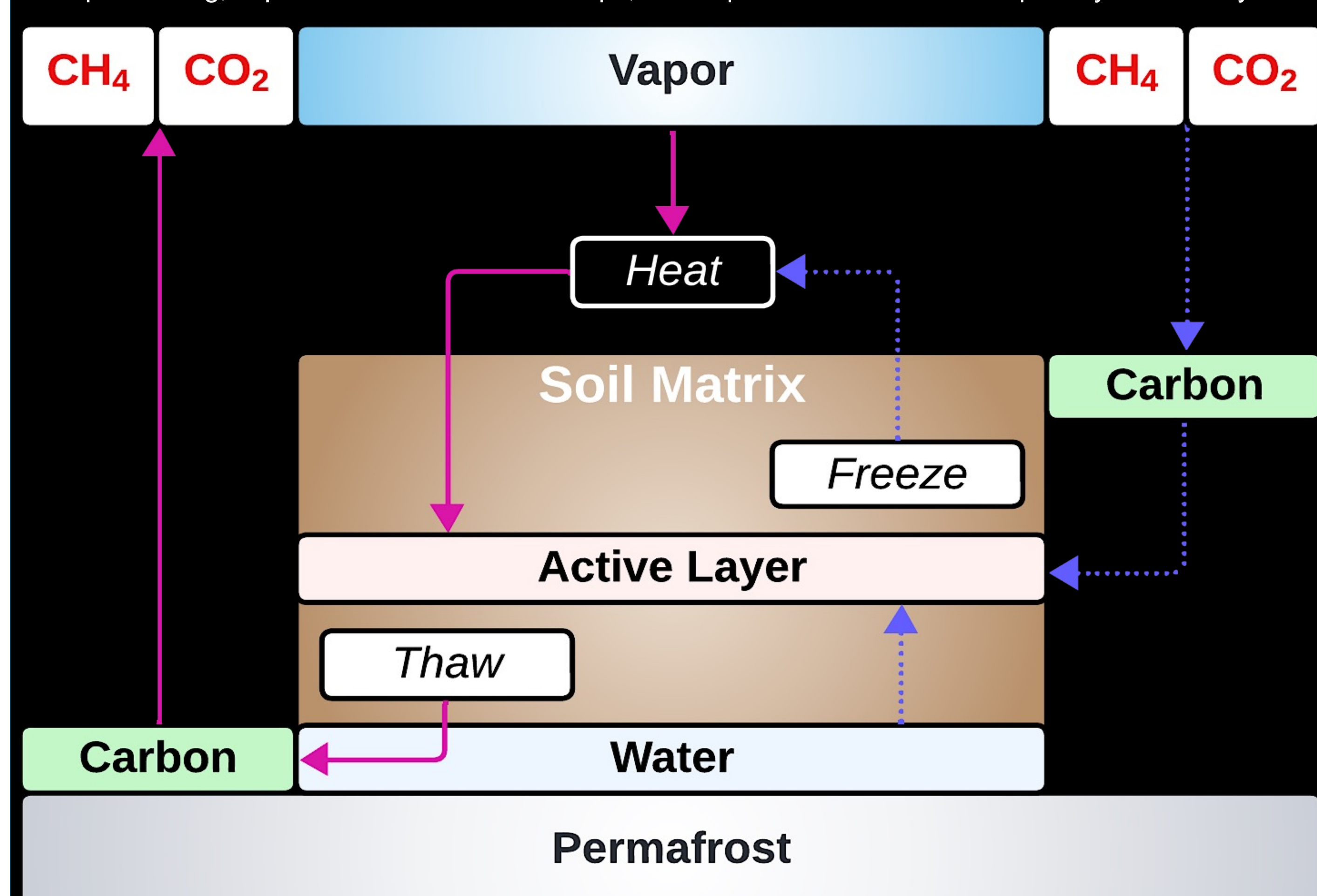
BACKGROUND

Complex non-linear relationships exist between the permafrost thermal state, active layer thickness, and terrestrial carbon cycle dynamics in Arctic and boreal Alaska. 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 and uncertainty of thaw-induced carbon release and feedback mechanisms challenge efforts to quantify the magnitude, rate, timing, composition, and extent of the permafrost carbon feedback (PCF; Miner et al., 2021), further complicating this issue. The PCF is an emerging phenomenon resulting from rising global temperatures due to climate change, accelerating permafrost degradation, increasing exposure of ancient carbon to microbial decomposition, leading to further amplification of warming.

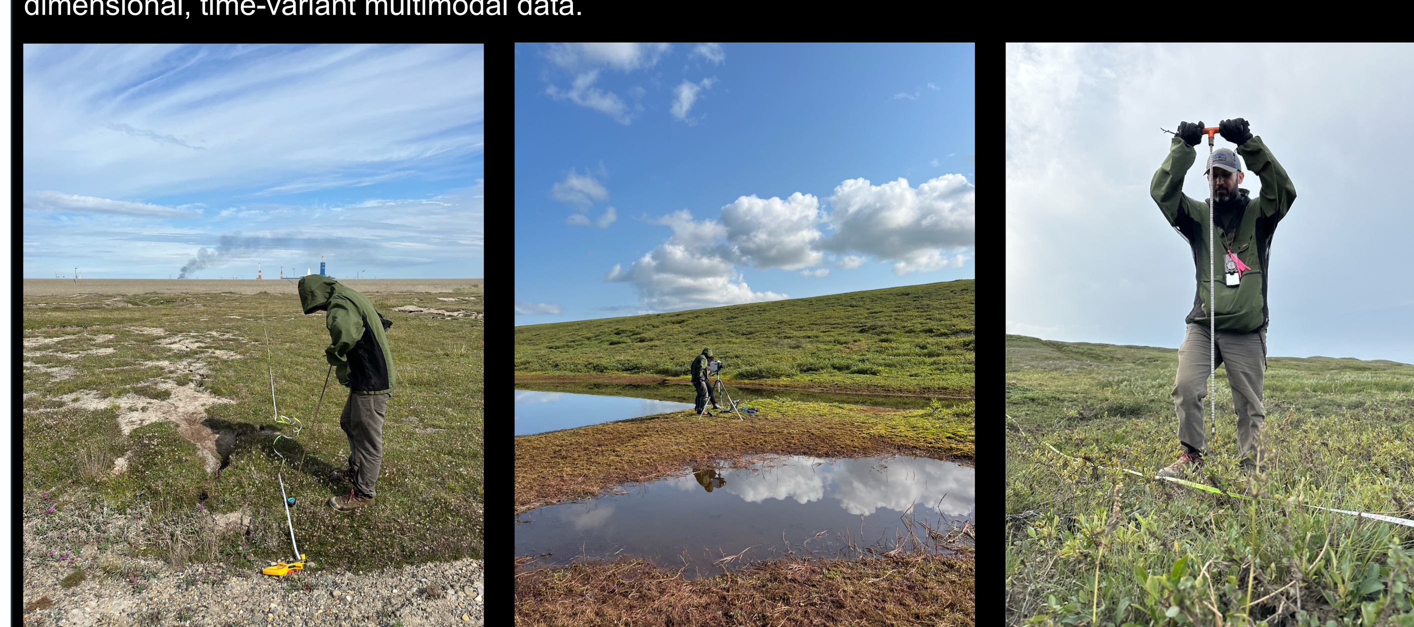
This research examines three challenges presented by the PCF: the big data problem, the remote sensing problem, and the modeling problem. First, (1) we are operating in a space of diametrically opposing issues to store, process, and analyze information over space and time, i.e., *dearth* of field data or an *over-abundance* of data acquired from remote sensing and modeling resources. Due to spatiotemporal limitations, instrument constraints, and other challenges in the high latitudes (e.g., frequent cloud cover, short summer periods, low illumination angles), (2) the ability to quantify or infer the magnitude, rate, and extent of the PCF and subsurface phenomena 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). Moreover, (3) subroutines and interactions governing earth system models 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). Fortunately, artificial intelligence (AI) optimizes complex earth system data processing, captures nonlinear relationships, and improves model skill and quantify uncertainty.



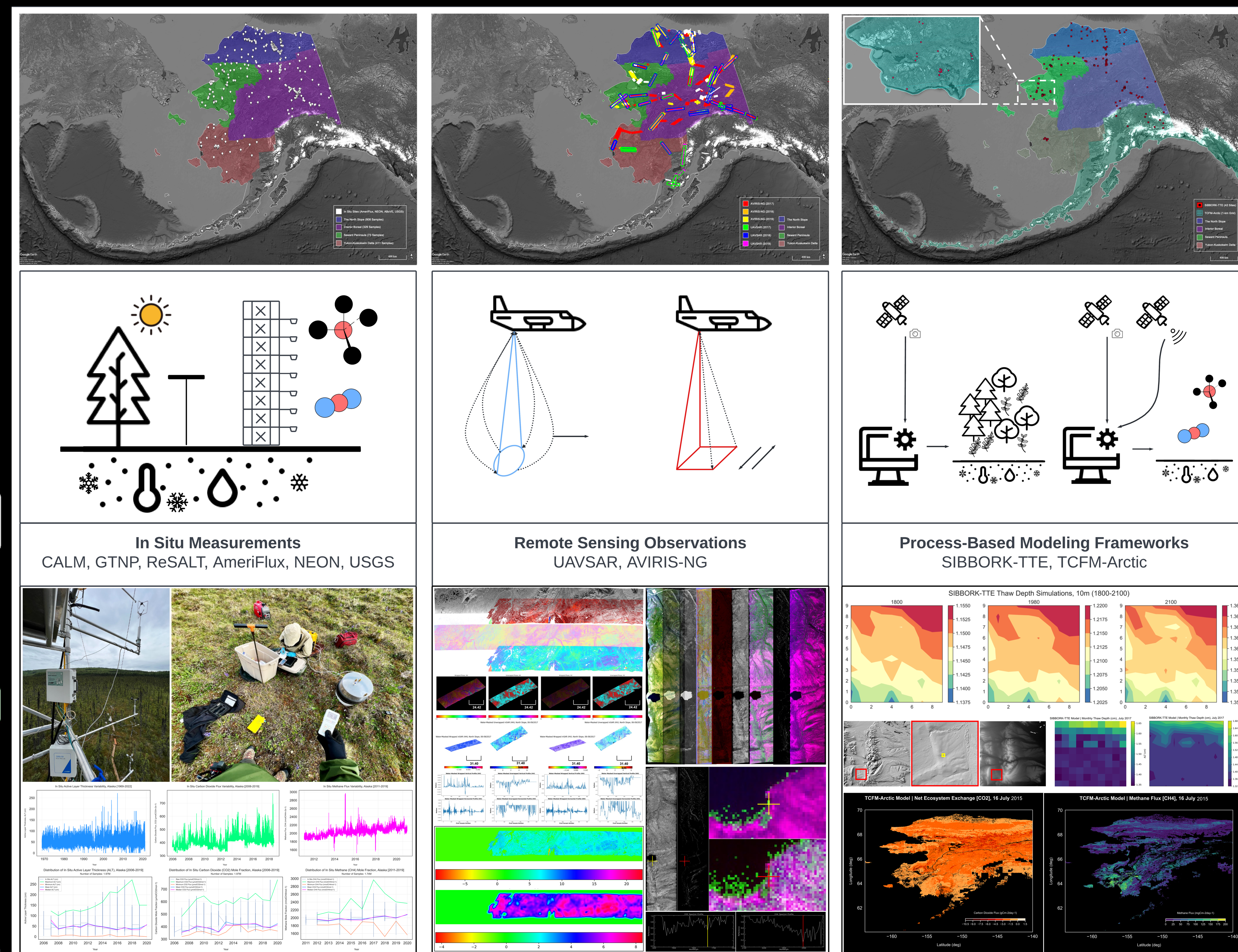
MOTIVATION

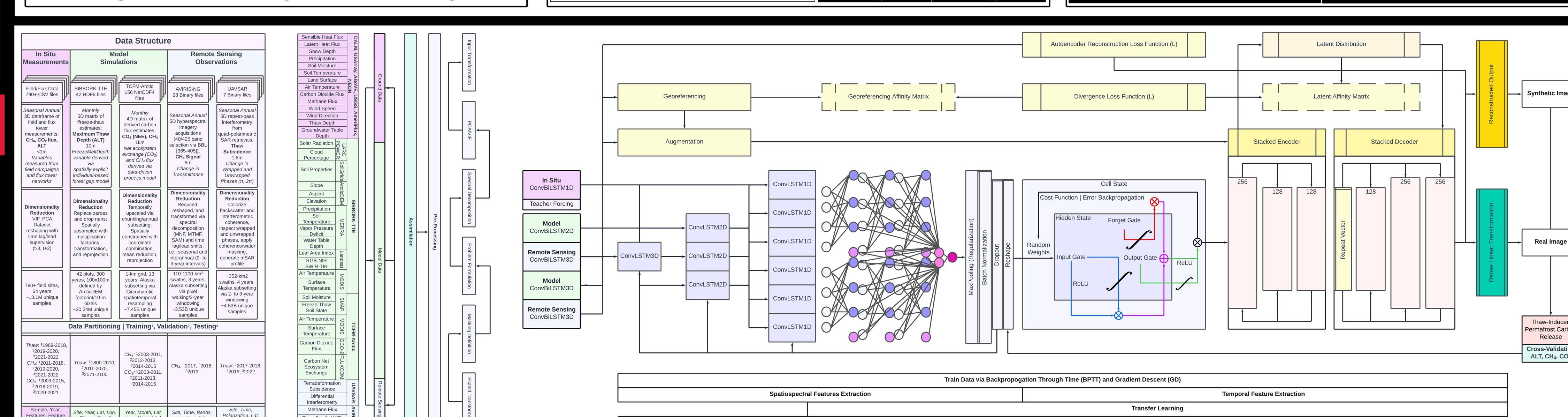
There is an urgent need to both understand *how* and *to what extent* permafrost degradation is destabilizing the Alaskan carbon balance, and to characterize the feedbacks involved. Therefore, the objective of this research is to reconcile these challenges (1-3) with AI, constrain these questions realistically in space and time and apply these solutions to scale, simulate, and disentangle the control factors and contributing drivers of the PCF signal.

The study domain consists 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). We leverage a hybridized multimodal ensemble learning formulation (GeoCryoAI) with 13.1M site-level in situ measurements, 8.06B remote sensing observations, and 7.48B modeling outputs across the Alaskan tundra and boreal landscapes. After transformation, dimensionality reduction, trend removal, time-delayed supervision, and regression analyses, model training initializes 12.4M parameters to simultaneously ingest and analyze high-dimensional, time-variant multimodal data.



METHODS





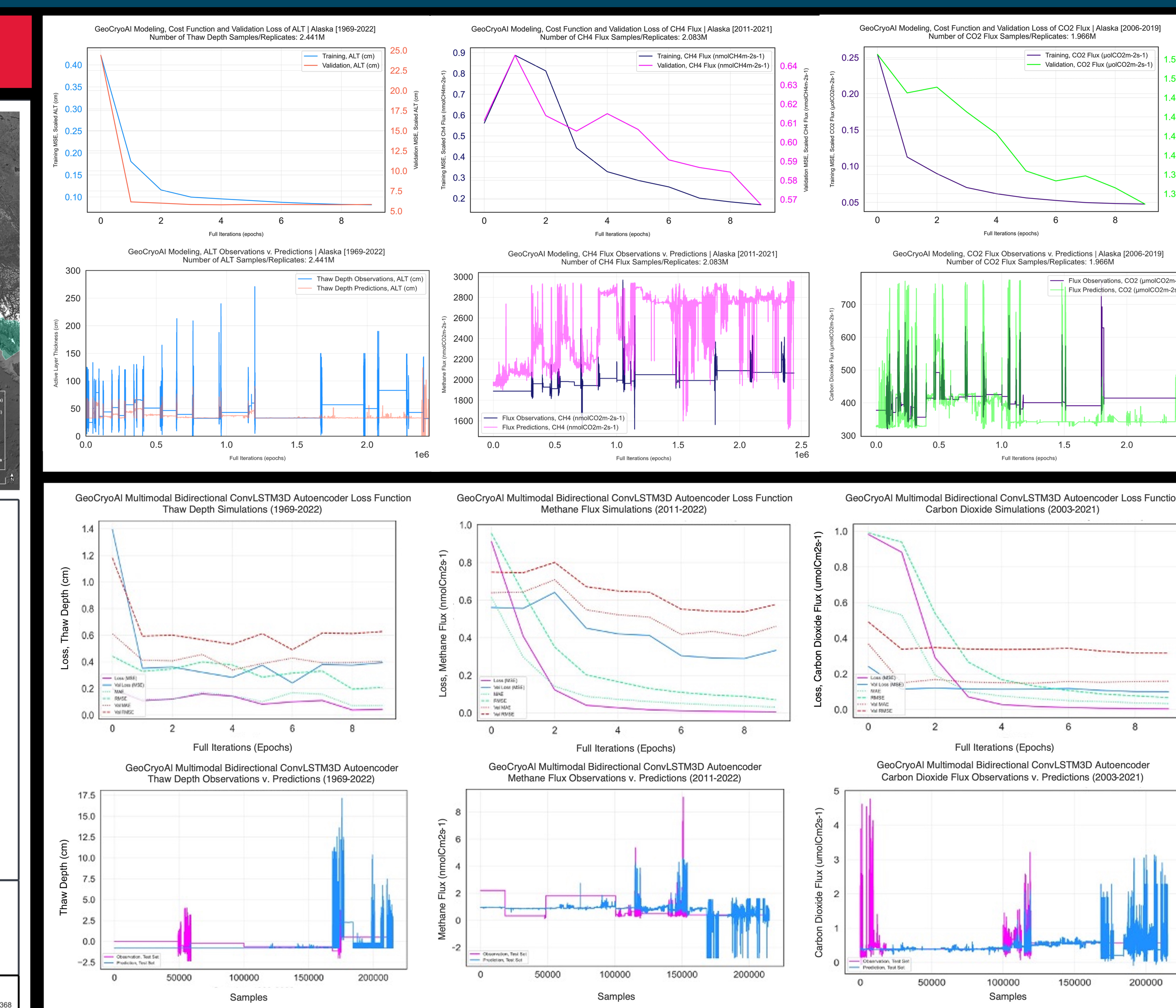
The GeoCryoAI architecture is constructed with a process-constrained ensemble learning hybridized framework of stacked convolutionally-layered long short-term memory-encoded recurrent neural networks optimized with a hyperparameter dictionary and a Bayesian Optimization search algorithm. Feedback nonlinearities 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). We compared teacher forcing and multimodal DA performance among time-delayed naïve persistence (baseline) regression and GeoCryoAI simulations of ALT, CH_4, and CO_2 yielding five error metrics derived from loss functions and predictions during training, validation, and testing over 10 epochs.

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

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

RESULTS | SIGNIFICANCE

GeoCryoAI simulations mirrored PCF dynamics across Alaska yielding promising results. With every epoch pass, validation loss is reduced. However, though validation and testing loss improved for CH_4, forecasting the CH_4 signal variability was a challenge during teacher forcing (i.e., failed to stabilize during periods of abrupt change of CH_4 and consistently overestimated CH_4 signal). By introducing more data into the framework, this discrepancy was ameliorated with limited changes to validation and testing loss. However, new changes emerged, i.e., failed to capture and predict early/initial pulses of thaw and CO_2 release. These results suggest the need for (1) more discriminant data partitioning (multitemporal coverage complexities, e.g., SAR), (2) further regularization (minimize weight aggregation), (3) more training (increase epochs), and/or (4) model is overfitting and may be resolved by simplifying network to aid generalizability. GeoCryoAI introduces ecological memory components and effectively captures and learns subtle spatiotemporal complexities as well as abrupt and persistent changes in high-latitude ecosystems by emulating permafrost degradation and carbon flux dynamics across Alaska with high precision and minimal loss (RMSE: 1.007cm, 0.694nmolCH_4m^{-2}s^{-1}, 0.213μmolCO_2m^{-2}s^{-1}). To our knowledge, this is the first time AI is applied to ameliorate dichotomy gaps while investigating the PCF phenomena combining ground, remote sensing, and modeling data.



	Active Layer Thickness (cm), 1969-2022	Methane (nmolCH_4m^{-2}s^{-1}), 2011-2022	Carbon Dioxide (μmolCO_2m^{-2}s^{-1}), 2003-2021
Naïve Persistence Model			
Test RMSE	1.997	0.884	1.906
GeoCryoAI I Teacher Forcing			
Test RMSE	1.327	0.715	0.697
Fractional Reduction	-33.55%	-19.12%	-63.43%
GeoCryoAI I Multimodality			
Test MAE	0.708	0.591	0.090
Test MSE	1.014	0.481	0.045
Test MAPE	0.578	0.510	0.156
Test RMSE	1.007	0.694	0.213
Fractional Reduction	-49.57%, -24.11%	-21.49%, -2.94%	-88.82%,-69.44%

Our approach overcomes traditional model inefficiencies and resolves spatiotemporal disparities, providing a novel methodology for assimilating contemporaneous information on scales from individual sites to the Pan-Arctic. GeoCryoAI ingests ~15.8B measurements and observations to learn, simulate, and forecast the primary constituents of the PCF with prognostic and retrospective capabilities. This is important to corroborate *how* permafrost degradation and thaw subsidence *affect* carbon loss by *conserving* energy balance. In addition, this study underscores the significance of thaw-induced climate change exacerbated by the PCF and highlights the importance of resolving spatiotemporal variability of ALT as a sensitive harbinger of change.

FUTURE WORK | PUBLICATIONS

Ongoing research elucidates on the PCF and delayed subsurface phenomena by (1) enrichment, i.e., 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) development, i.e., generating Circumarctic zero-curtain space-time maps to distribute to 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, and regional levels (e.g., critical infrastructure damage, cultural vulnerabilities). Datasets and codebases are distributed in a GitHub repository.

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