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Quantifying Permafrost Carbon Dynamics with Feedback Neural Networks and Ecological Memory

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Abstract

It is well-established that feedbacks between permafrost degradation and the release of soil carbon into the atmosphere impact land-atmosphere feedback mechanisms, 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 earth system models do not account for permafrost carbon feedback mechanisms; therefore, we are exploring, simulating, and quantifying this limitation with field-scale surveys and numerical modeling, image processing, and machine learning at scale across the tundra and boreal landscape in Alaska. This research study seeks to identify, interpret, and explain the causal links and feedback sensitivities attributed to permafrost degradation and terrestrial carbon cycling disruption with a hybridized multimodal deep learning ensemble of stacked convolutionally-layered, memory-based bidirectional recurrent neural networks (GeoCryoAI). This framework integrates teacher forcing with in situ measurements and flux tower observations during the training process while bridging remote sensing imagery, model simulations, and reanalysis products for gap-filling purposes. Preliminary experiments to quantify, validate, and forecast permafrost degradation and carbon efflux across four subdomains in Alaska yield promising results, demonstrating the fidelity of this data-driven architecture. More specifically, GeoCryoAI effectively learns the behavior of these covariates with great precision and predicts permafrost degradation and carbon efflux with root mean square errors of 0.12385cm, 0.23745μmolCO$_2$mol^{-1}, and 0.29968nmolCH$_4$m^{-2}s^{-1}, respectively. Ongoing work demonstrates the fidelity of monitoring ALT variability as a sensitive harbinger of change, a unique signal characterizing permafrost degradation, soil carbon flux, and other biogeochemical drivers facilitating land cover change and earth system feedback. These multimodal approaches to knowledge discovery will improve sensitivity analyses, disentangle the spatial processes and causal links behind drivers of change, and reconcile disparate estimations and below-ground uncertainty across the Arctic system.

Introduction

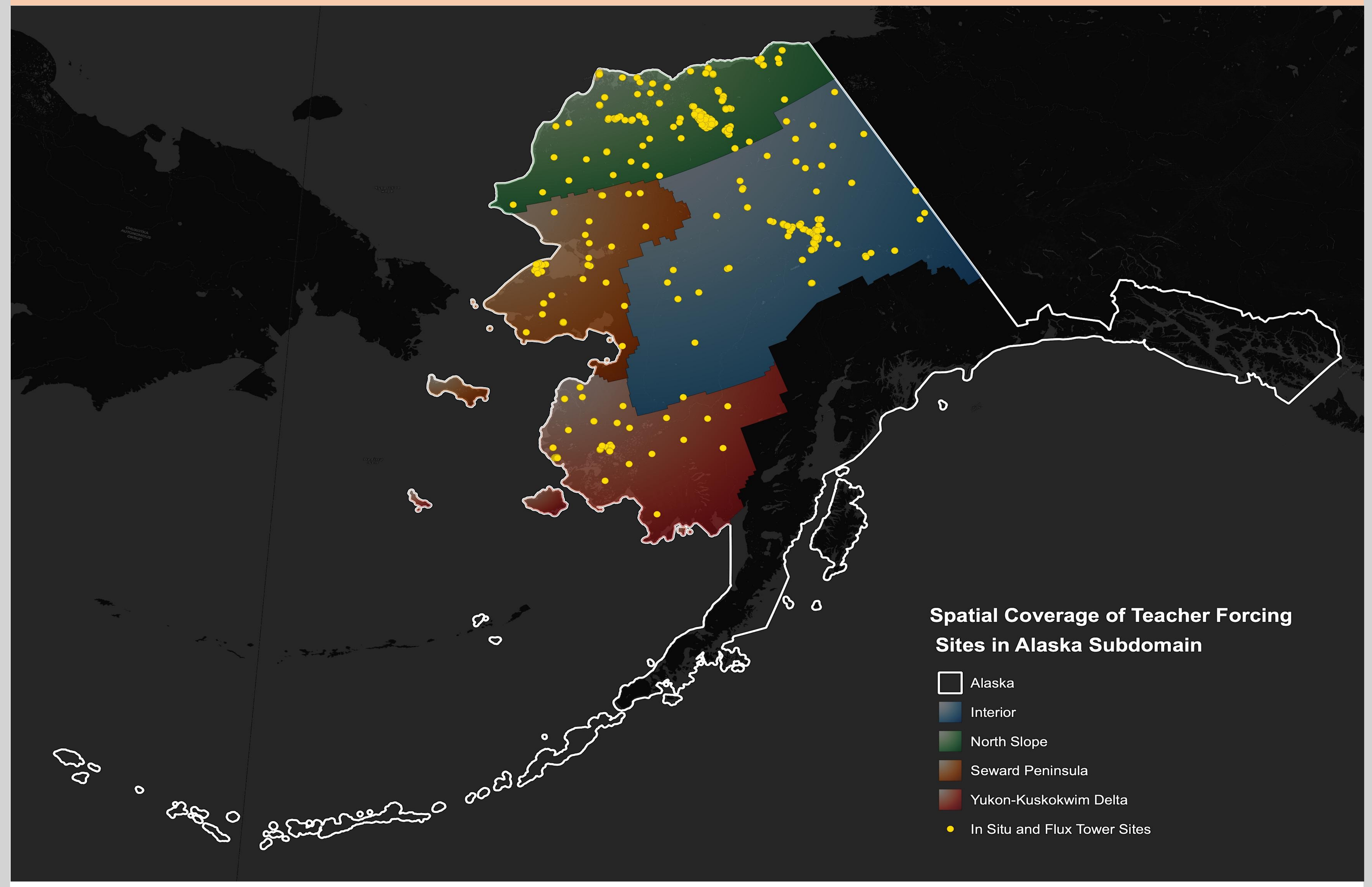
Across the circumpolar arctic, quantifying the persistent irregularities and expansive impacts characterizing permafrost degradation remain scientific challenges. These irregularities constitute a spatiotemporal disruption in the transitional state of permafrost, with abrupt thawing triggers seasonal ground subsidence, thermokarst and thaw lake formation, and the proliferation of new wetlands, ponds, and intricate hydrologic networks with potential methane emission hotspots near littoral zones (Olefeldt, D., et al. 2016; Jorgenson, M.T., et al. 2006; Jorgenson, M.T., et al. 2013; Walter, K.M., et al. 2007; Klapstein, S.J., et al. 2014; Turetsky, M.R., et al. 2014). Model projections suggest attribution of top-down permafrost degradation and soil carbon decomposition to carbon-climate feedback patterns will continue for nearly two centuries (Koven, C.D., et al. 2011; McGuire, A.D., et al. 2018). Permafrost dynamics are relevant to the global community because this frozen carbon-rich soil matrix characterizes nearly 14 million square kilometers of the global terrestrial surface, with total soil organic carbon stock estimates near 1.30±0.20 EgC (Hugelius, G. et al. 2014). The permafrost carbon feedback not only qualifies as a climate change catalyst but also quantitatively amplifies land-atmosphere coupling and localized warming patterns, disrupts carbon cycle partitioning, and destabilizes feedback thresholds. To quantify and interpret this feedback, it is important to understand the *mechanics* behind frost heave-thaw dynamics, moisture signaling, and terrestrial carbon flux. These components vary in space and time, presenting sequential problems to investigate within the earth system. This research study explores the integration of recurrent feedback neural networks throughout the data assimilation process. This architecture attempts to resolve spatiotemporal disparities and unify multimodal approaches to more accurately capture real-world dynamics and reflect these abrupt and persistent changes in the arctic (i.e., teacher forcing harnesses in situ observations and eddy covariance measurements during model training); the hidden state, loss function, and output of the recurrent system is contextualized following this equation:

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

Recurrent neurons receive two impulses and two sets of weight matrices (Wx,Wy) at each time step (t): an input signal (X) and an output vector (y) from the previous time step (t-1). The resulting encoded matrix (i.e., memory cell) is a function of X(t) and Y(t-1) derived from the signals, weights, activation function (∅), and bias vector (b). In addition, the cell state is denoted as a function of inputs from a hidden layer existing at a previous time step (i.e., h_((t))=f(h_((t-1)),x_((t)))) (Körner, M., et al. 2021). These chaotic linearly recursive neural networks develop internal dynamics through time, combining the previous time step and hidden representation into a learned representation at the current time step.

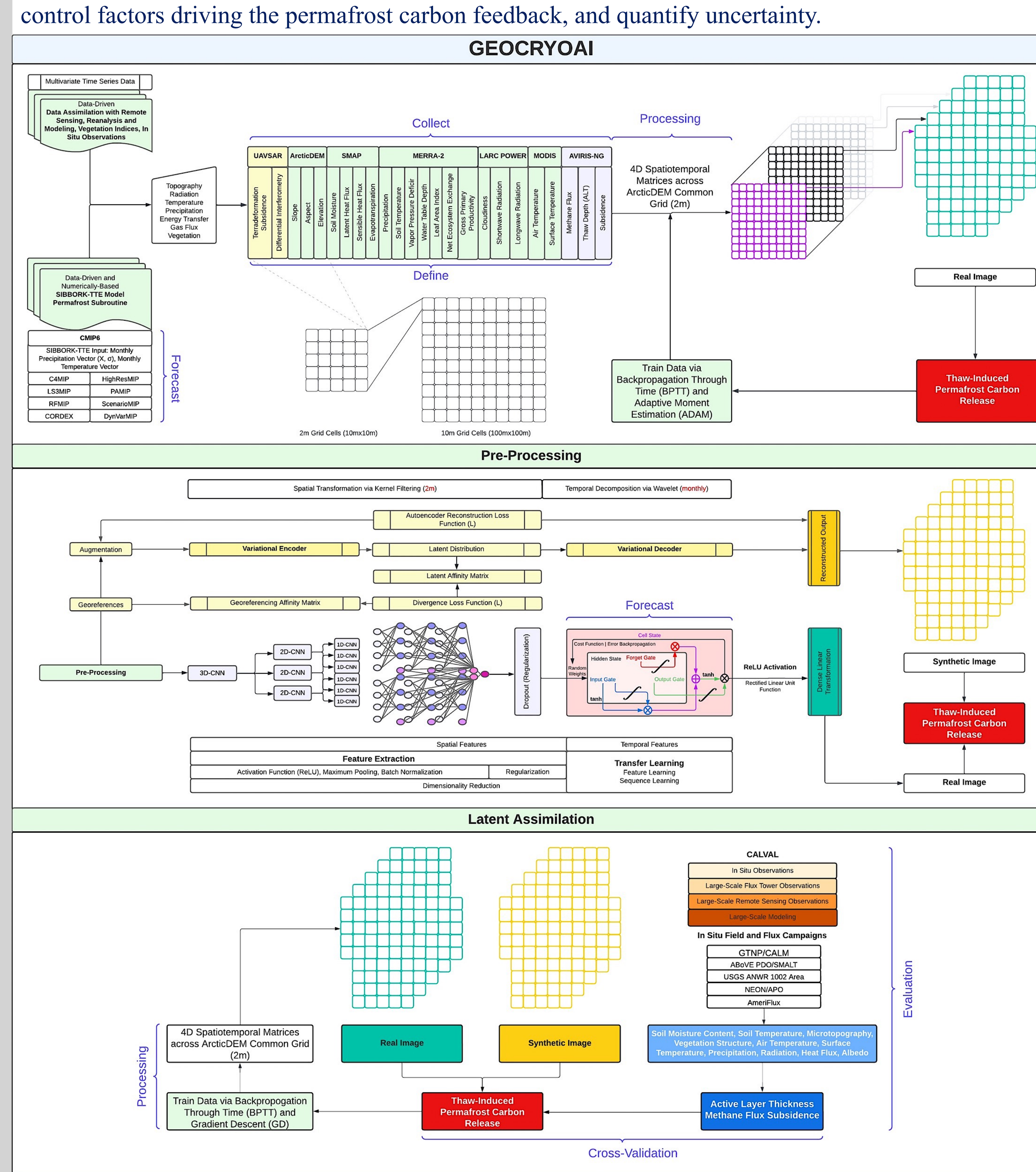
Across these four subdomains in Alaska, nearly 32.7 million point-based grids, transects, and replicates were sampled and synthesized from more than 790 field sites. Many of these measurements were derived from the FLUXNET and NEON flux tower observation networks and comprise a significant contribution to flux and belowground dynamics in real-time in recent history. Alternatively, the CALM and GTNP active layer monitoring campaigns demonstrate a wide temporal coverage. These in situ originating from various flux tower networks and field campaigns include several critical environmental covariates such as precipitation, wind speed and direction, surface and air temperature, soil moisture content, soil temperature, active layer thickness, water table depth, methane flux, carbon dioxide mole fraction, soil organic carbon, and other meteorological and biogeochemical observations. These measurements were harvested, preprocessed, and injected as input into the model for training (i.e., teacher forcing embedded network).

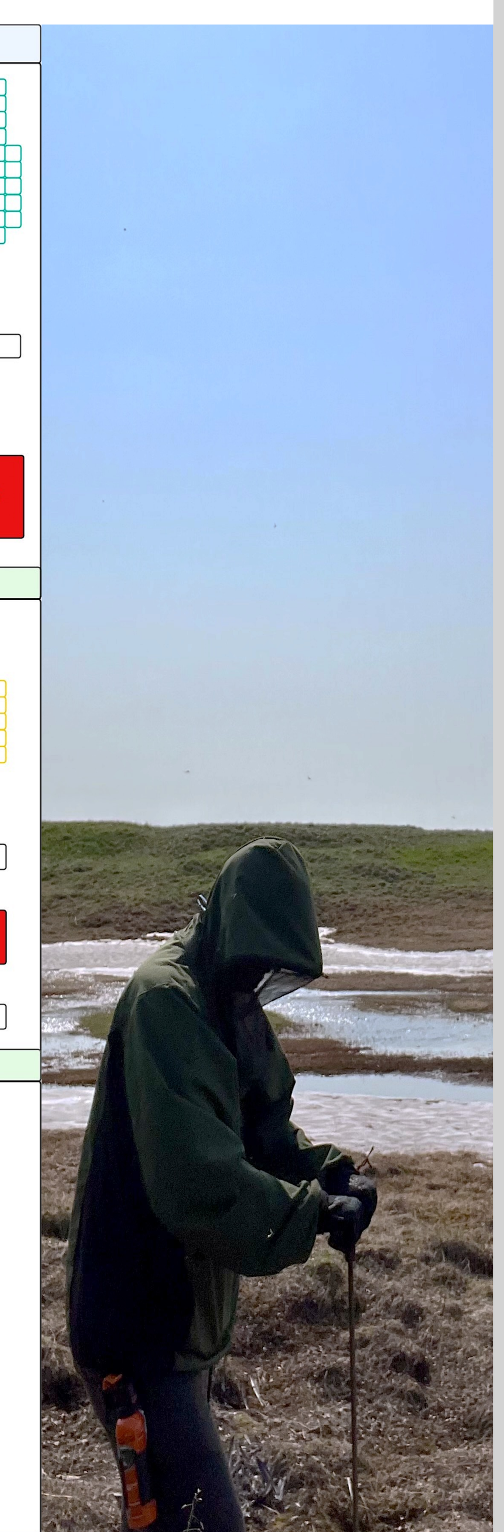
Materials and Methods



Alaska subdomain of interest (ROIs) include the Interior, North Slope, Seward Peninsula, and Yukon-Kuskokwim Delta. Imagery attribution: Google SIO, NOAA, US Navy, NGA, GEBCO Landsat/Copernicus IBCAO Data LDEO-Columbia, NSF, NOAA).

GeoCryoAI is a state-of-the-art deep learning algorithm tailored to assimilate remote sensing information and uncover previously hidden patterns for permafrost-affected landscapes. This data-driven strategy will identify, interpret, and explain the causal links and feedback sensitivities attributed to permafrost degradation and terrestrial carbon cycling imbalance with a hybridized deep learning ensemble of memory-based recurrent networks and a multimodal composite of in situ and tower measurements, remote sensing observations, reanalysis and modeling outputs, and assimilation that formulates the GeoCryoAI architecture. The architecture seeks to capture abrupt and persistent changes in subsurface conditions, identify the extent of prolonged respiration patterns into the cold season, disentangle control factors driving the permafrost carbon feedback, and quantify uncertainty.

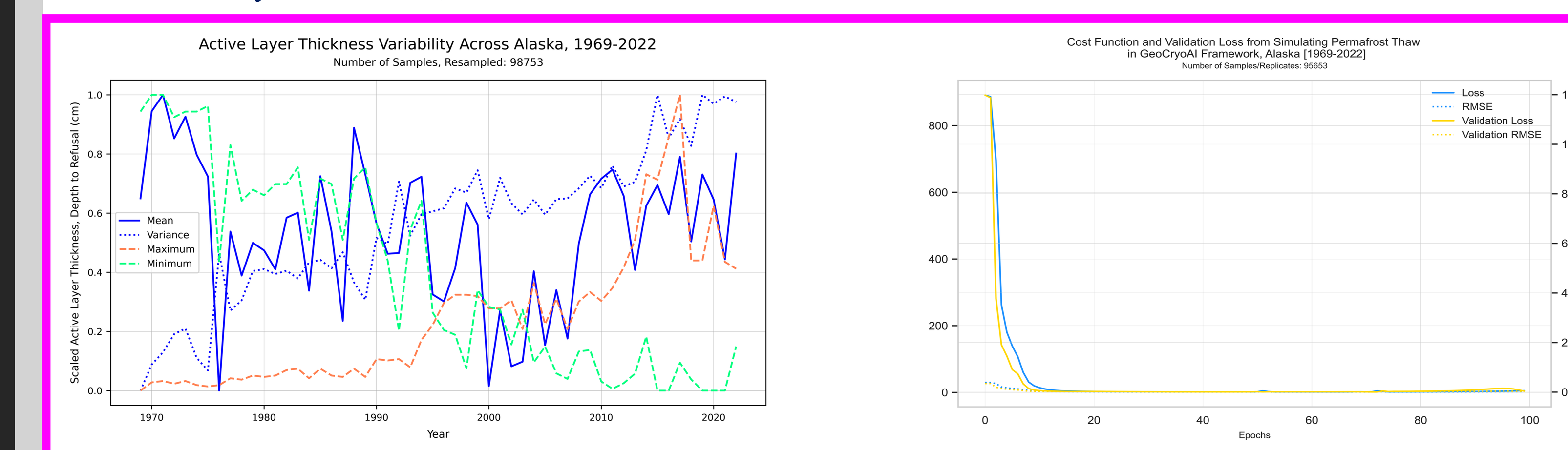




Results and Discussion

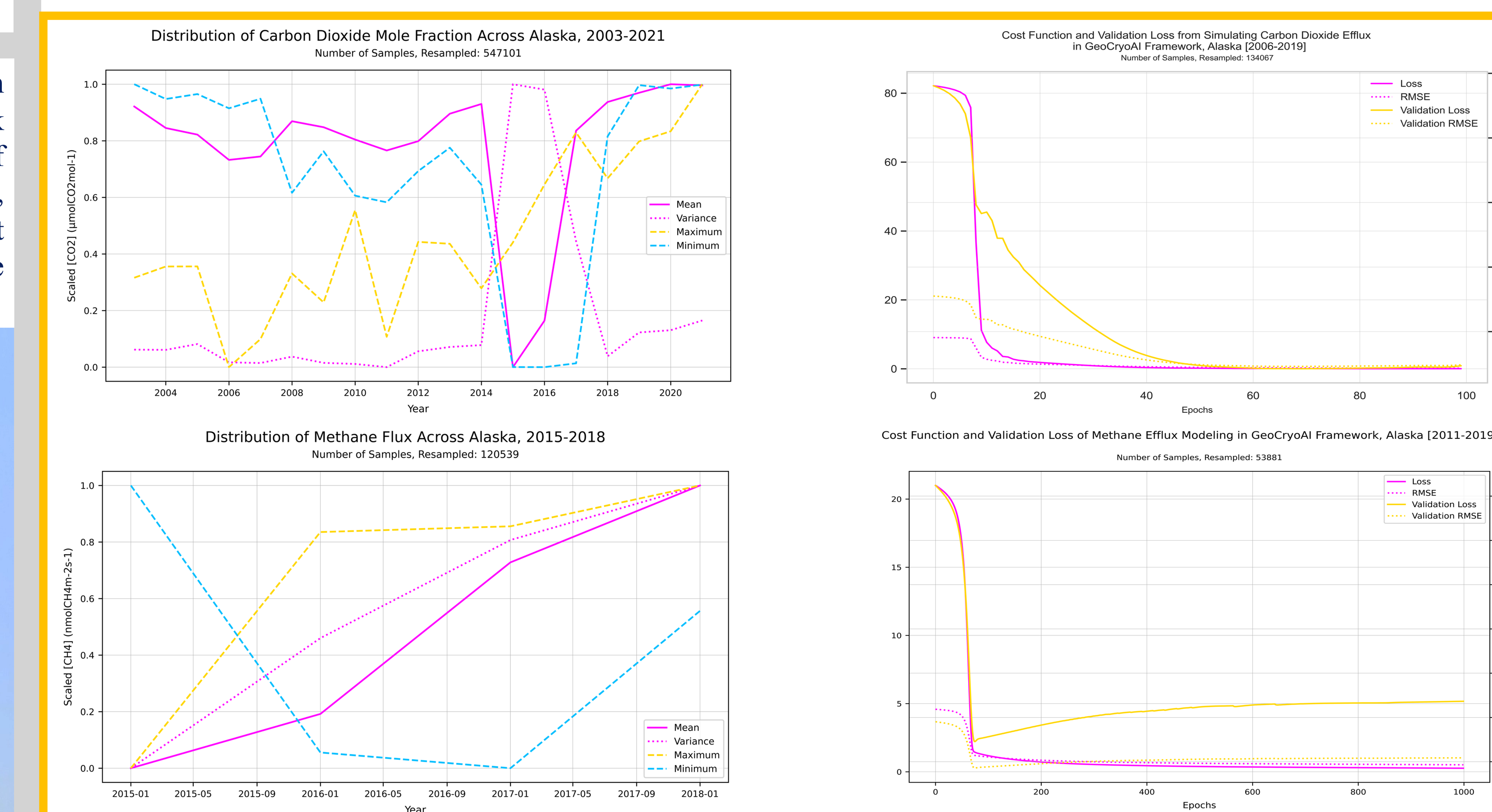
Permafrost Degradation

GeoCryoAI thaw simulations with site-level teacher forcing via in situ and flux tower observations of monthly mean active layer thickness, 1969-2022.



Carbon Release

GeoCryoAI carbon efflux simulations with site-level teacher forcing via in situ and flux tower observations of half-hourly carbon dioxide mole fraction [CO2_1_1_1] and methane flux [FCH4_2] sampling, 2003-2021.



GeoCryoAI simulations with site-level teacher forcing via in situ and flux observations of annual active layer thickness (1969-2022) and carbon flux measurements (2003-2021). These results indicate persistent trends with increasing permafrost degradation and soil carbon release, displaying statewide prediction error (RMSE) for thaw and carbon efflux at 0.12385cm, 0.23745μmolCO$_2$mol^{-1}, and 0.29968nmolCH$_4$m^{-2}s^{-1}, respectively. Regional analyses and uncertainty quantification is forthcoming. This systematic methodology generates cross-cutting deliverables that maximize in situ observations and bridge fine-scale process-based multimodal resolutions, historical observations and future projections, and a suite of legacy toolkits and novel computing approaches. These high-resolution products may further elucidate subsurface dynamics, thaw, terrestrial carbon cycle disruption, and coupling sensitivities under a changing climate. Ongoing investigations include quantifying uncertainty with multivariate mutual information and transfer entropy as well as synthesizing airborne remote sensing data in preparation for generating circumpolar space-time zero-curtain maps informed by upcoming spaceborne missions (NISAR, TRISHNA, LSTM LST, SBG TIR FF).

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