Quantifying Feedback Sensitivities of Permafrost Degradation and Carbon Release with Earth Observation Data and Feedback Neural Networks

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December 31, 2022

Abstract

It is well-established that positive 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. Permafrost dynamics are relevant to the global community because the distribution of this frozen ground substrate characterizes nearly 23 million square kilometers of the northern latitudes. The widespread distribution of thawing permafrost is causing a cascade of geophysical and biochemical disturbances with global impact. Current earth system models do not account for permafrost carbon feedback mechanisms; 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 taiga ecosystems (TTE). This research seeks to identify, interpret, and explain the causal links and feedback sensitivities attributed to permafrost degradation and terrestrial carbon cycling asymmetry with in situ observations, remote sensing imagery, modeling and reanalysis products, and a hybridized multimodal deep learning ensemble of recurrent, convolutionally-layered, memory-based networks (GeoCryoAI). Preliminary metrics obtained from mirroring freeze-thaw dynamics and soil carbon flux across four subdomain in Alaska yield a root mean square error of 6.3637 and 4.7973, respectively. More specifically, this data-driven modeling ensemble is composed of a convolutional neural network-filtered (CNN) long short-term memory-encoded (LSTM) recurrent neural network that integrates teacher learning from in situ observations while embedding satellite-based measurements and time series datasets into a network of activation functions and processing layers. These outputs are then trained within a variational autoencoder framework (VAE) that encodes and imputes proper decoding protocol necessary for generative adversarial training, benchmarking, and reconstructing synthetic time series data for gap-filling and feature learning. Ongoing work demonstrates the fidelity of monitoring active layer thickness (ALT) variability as a sensitive, silent-but-pronounced harbinger of change; a unique signal for characterizing and forecasting permafrost degradation, soil carbon flux, and other biogeochemical drivers facilitating land cover change and earth system feedbacks. These multimodal approaches to knowledge discovery will not only improve sensitivity analyses and disentangle the spatial processes and causal links behind drivers of change, but also reconcile disparate estimations and below-ground uncertainty across the Arctic system.

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Abstract

It is well-established that positive 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. Permafrost dynamics are relevant to the global community because the distribution of this frozen ground substrate characterizes nearly 23 million square kilometers of the northern latitudes. The widespread distribution of thawing permafrost is causing a cascade of geophysical and biochemical disturbances with global impact. Current earth system models do not account for permafrost carbon feedback mechanisms; we are exploring, simulating, and quantifying this limitation with field-scale surveys (i.e., landscape characterization, thermo-erosional features and gullies, active layer depth, and cryostructures) and numerical modeling, image processing, and machine learning at scale across the tundra and boreal ecosystems (TTE). This research seeks to identify, interpret, and explain the causal links and feedback sensitivities attributed to permafrost degradation and terrestrial carbon cycling asymmetry with in situ observations, remote sensing imagery, forest gap modeling (SIBBORK-TTE), multimodal data assimilation architecture, and a hybridized deep learning ensemble of recurrent, convolutionally-layered, memory-based networks (GeoCryoAI). Preliminary metrics obtained from mirroring freeze-thaw dynamics and soil carbon flux across four subdomain in Alaska yield a root mean square error of 6.3637 and 4.7973, respectively. More specifically, this data-driven modeling ensemble is composed of a convolutional neural network-filtered (CNN) long short-term memory-encoded (LSTM) recurrent neural network that integrates teacher learning from in situ observations while embedding satellite-based measurements and time series datasets into a network of activation functions and processing layers. These outputs are then trained within a variational autoencoder framework (VAE) that encodes and imputes proper decoding protocol necessary for generative adversarial training, benchmarking, and reconstructing synthetic time series data for gap-filling and feature learning. Ongoing work demonstrates the fidelity of monitoring ALT variability as a sensitive, silent-but-pronounced harbinger of change; a unique signal for characterizing and forecasting permafrost degradation, soil carbon flux, and other biogeochemical drivers facilitating land cover change and earth system feedbacks. These multimodal approaches to knowledge discovery will not only improve sensitivity analyses and disentangle the spatial processes and causal links behind drivers of change, but also reconcile disparate estimations and below-ground uncertainty across the Arctic system.

Introduction

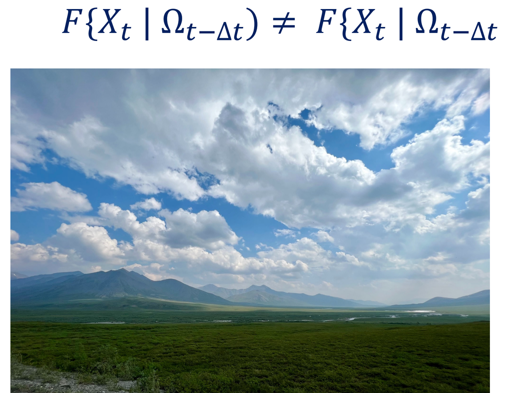
Across the circumpolar arctic, quantifying the persistent irregularities and expansive impacts characterizing permafrost degradation remain scientific challenges. These irregularities constitute a spatiotemporal disruption in the transitional state of permafrost, with abrupt thawing triggers seasonal 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 following the Stefan- Boltzmann Law:

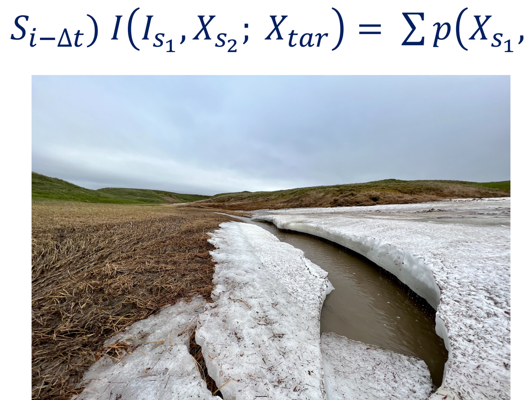
$$R = \sigma e T^4$$

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:

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

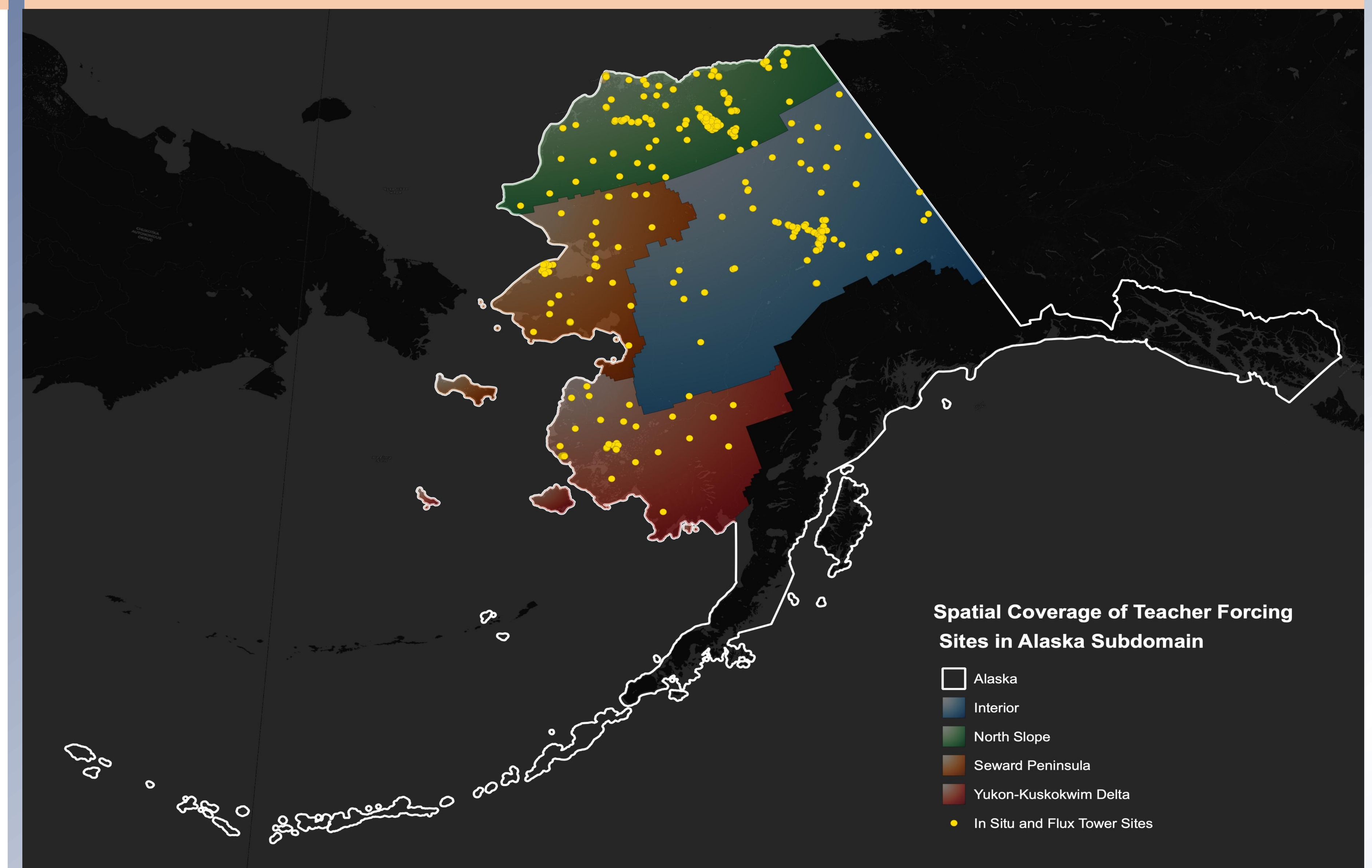
$$F\{X_t \mid \Omega_{t-\Delta t}\} \neq F\{X_t \mid \Omega_{t-\Delta t} - S_{i-\Delta t}\}\ I(I_{s_1}, X_{s_2}; X_{tar}) = \sum p(X_{s_1}, X_{s_2}, X_{tar}) \log_2 \left[\frac{p(X_{s_1},X_{s_2},X_{tar})}{p(X_{s_1},X_{s_2})\,p(X_{tar})}\right]$$





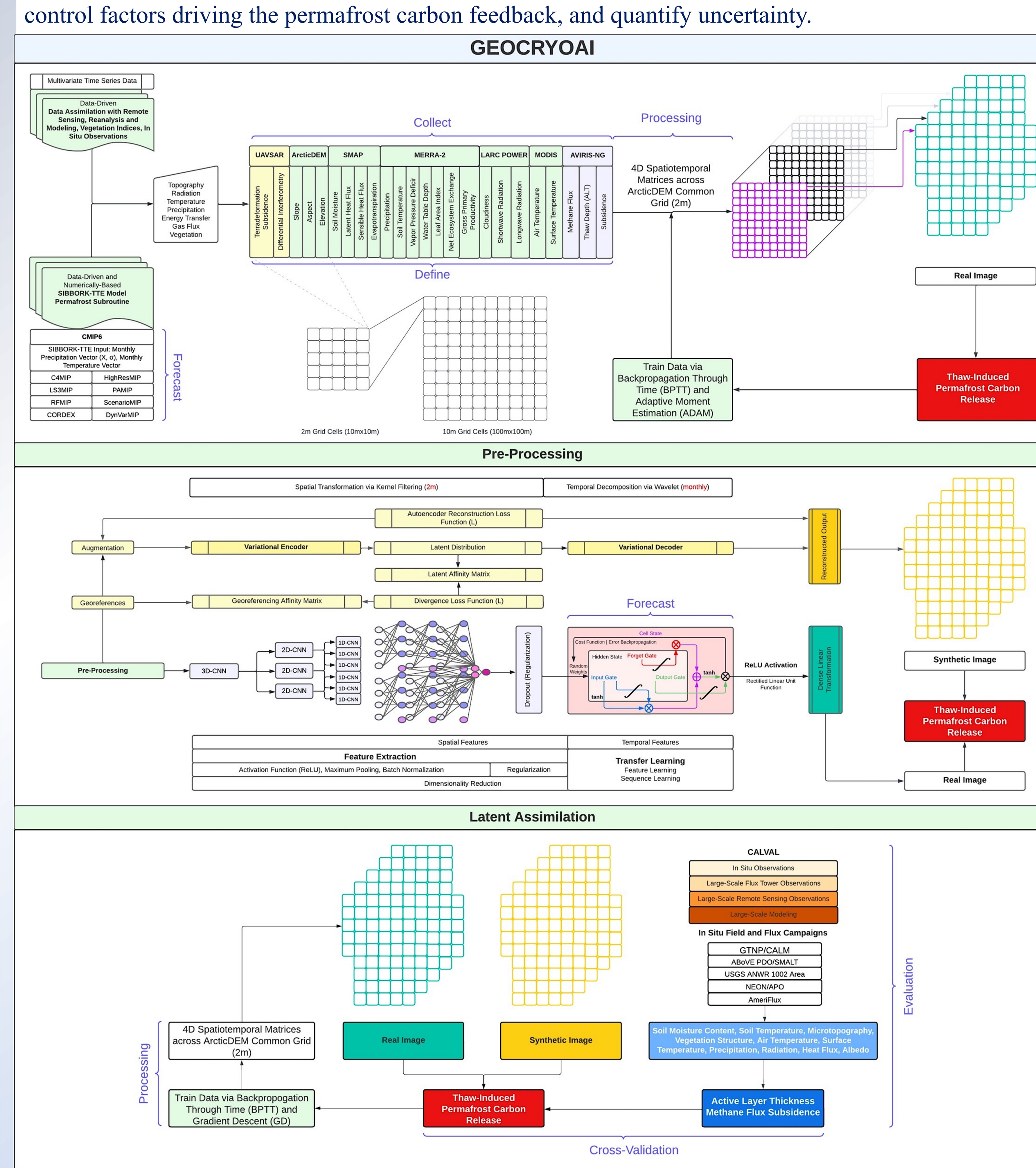
Throughout the model training process, nearly 21 million in situ and flux tower were extracted and tabulated from various networks and campaigns. These point-based, transect, and grid sampling protocols and replicates across Alaska inform and reinforce teacher forcing, e.g., GTNP, CALM, ABoVE, AmeriFlux, NEON. These measurements include covariates such as precipitation, air/surface temperature, soil moisture/temperature at depth, active layer thickness, water table depth, and carbon flux observations (e.g., methane and carbon dioxide flux/concentration, soil organic carbon). Additional field observations were gathered in July 2022 at some of the sites pictured above, including Chandalar Shelf and Eitel Sites (Brooks Range), 1002 Area (ANWR), and Eight Mile Lake.

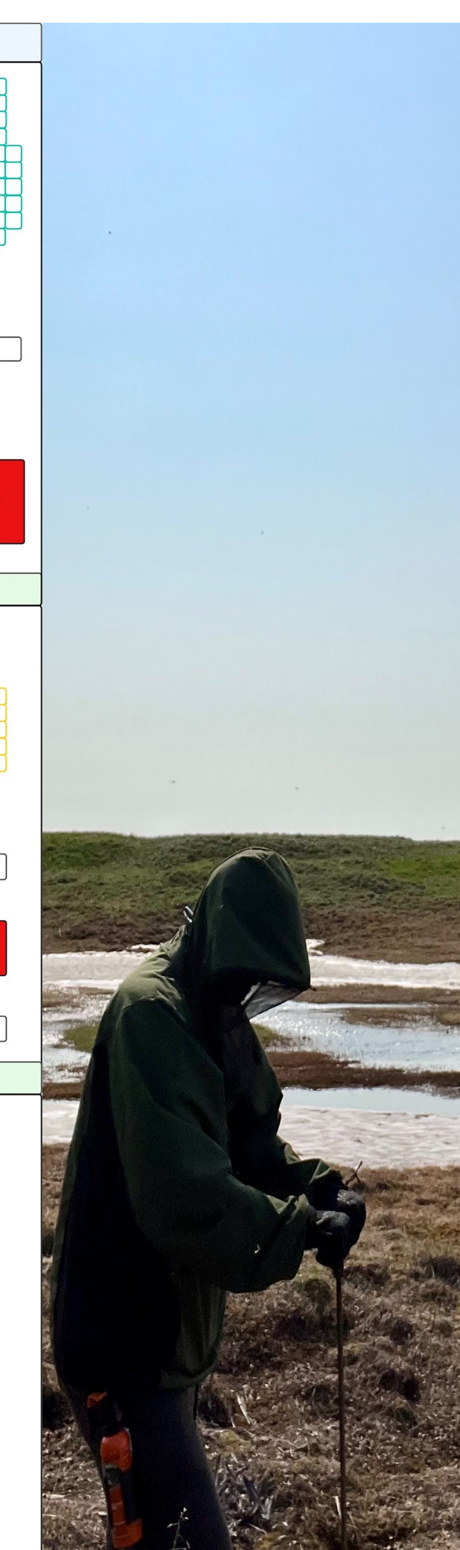
Methods



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.

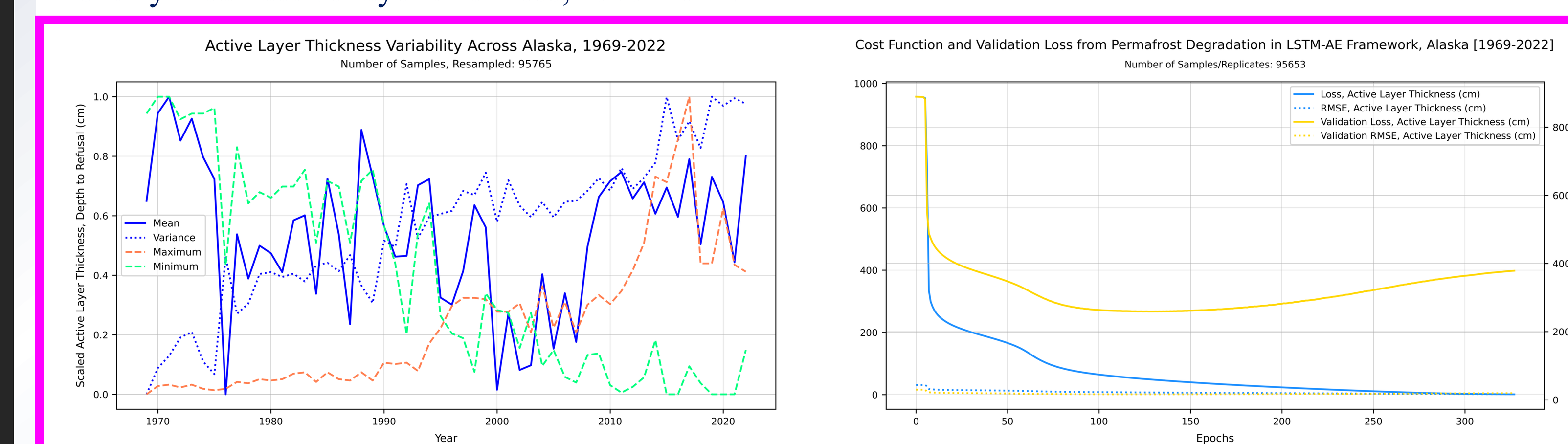




Results and Discussion

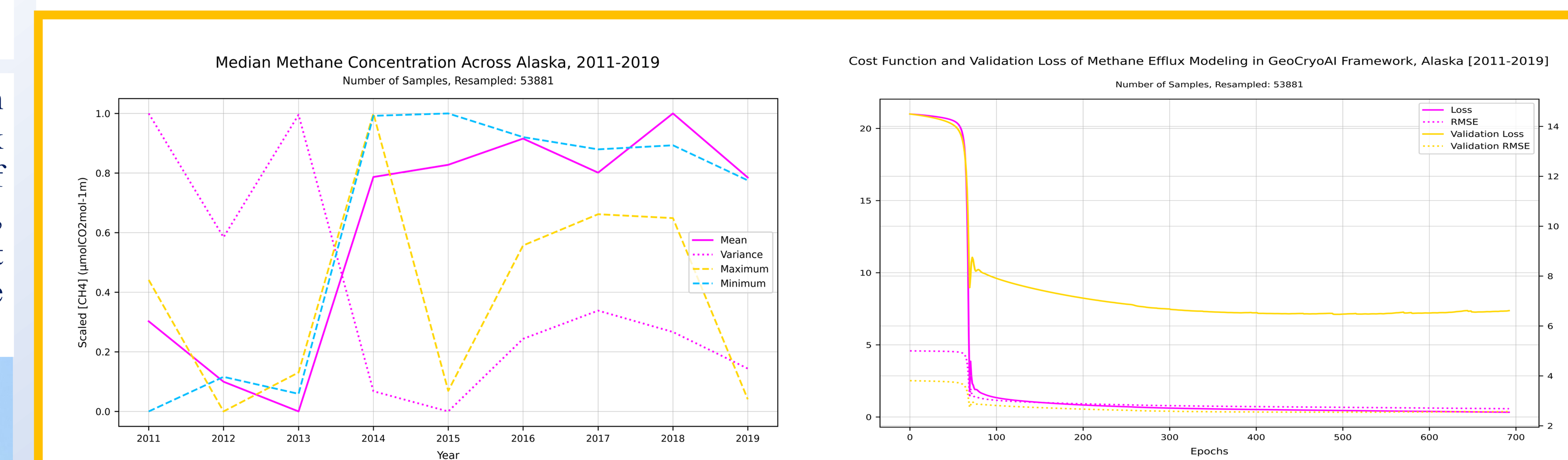
Permafrost Degradation

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 methane efflux [CH4] simulations with site-level teacher forcing via in situ and flux tower observations of half-hourly median methane concentration, 2011-2019.



GeoCryoAI simulations with site-level teacher forcing via in situ and flux observations of monthly maximum active layer thickness (1969-2022) and half-hour carbon flux measurements (2011-2019). Preliminary results indicate persistent trends with increasing permafrost degradation and soil carbon release, displaying statewide prediction error (RMSE) for permafrost thaw (cm) and carbon efflux ($\mu molCH_4 mol^{-1}m$) at 6.3637 and 4.7973, respectively. Regional analyses and uncertainty quantification is forthcoming. This systematic methodology generates cross-cutting deliverables that maximize in situ observational data and bridge fine-scale processes with 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, permafrost degradation, terrestrial carbon cycle disruption, and coupling sensitivities to climate change scenarios. 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).

Acknowledgements

I acknowledge and owe gratitude to the Alaska First Nations and Indigenous Peoples of Alaska upon whose traditional and ancestral lands I worked this summer (Inupiat, Gwich'in Nành, Dënéndeh, Koyukon, Tanana). Much appreciation is extended to my mentors and dissertation committee members - Dr. John J. Qu, Dr. Amanda H. Armstrong, Dr. Andreas E. Züfle, Dr. Paul A. Dirmeyer, and Dr. Konrad J. Wessels - in addition to a plethora of research and support scientists from the departments of Geography and Geoinformation Science and Atmospheric, Oceanic, and Earth Sciences at George Mason University. Furthermore, special thanks to the following institutions and campaigns for permitting field surveying, granting data accessibility rights and privileges, and providing such pivotal help and research potential over the past four years: NASA GSFC, NASA JPL, NASA ABoVE, NASA North American Carbon Program, USGS water and critical landscape characterization teams, USGS Earth Resources Observation and Science Center, Universities Space Research Association, University of Alaska at Fairbanks, University of Virginia, Northern Arizona University, George Washington University, University of Colorado, Woodwell Climate Research Center, ARCUS, United States Permafrost Association, and the CALM, FLUXNET, and NEON observatory networks.

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