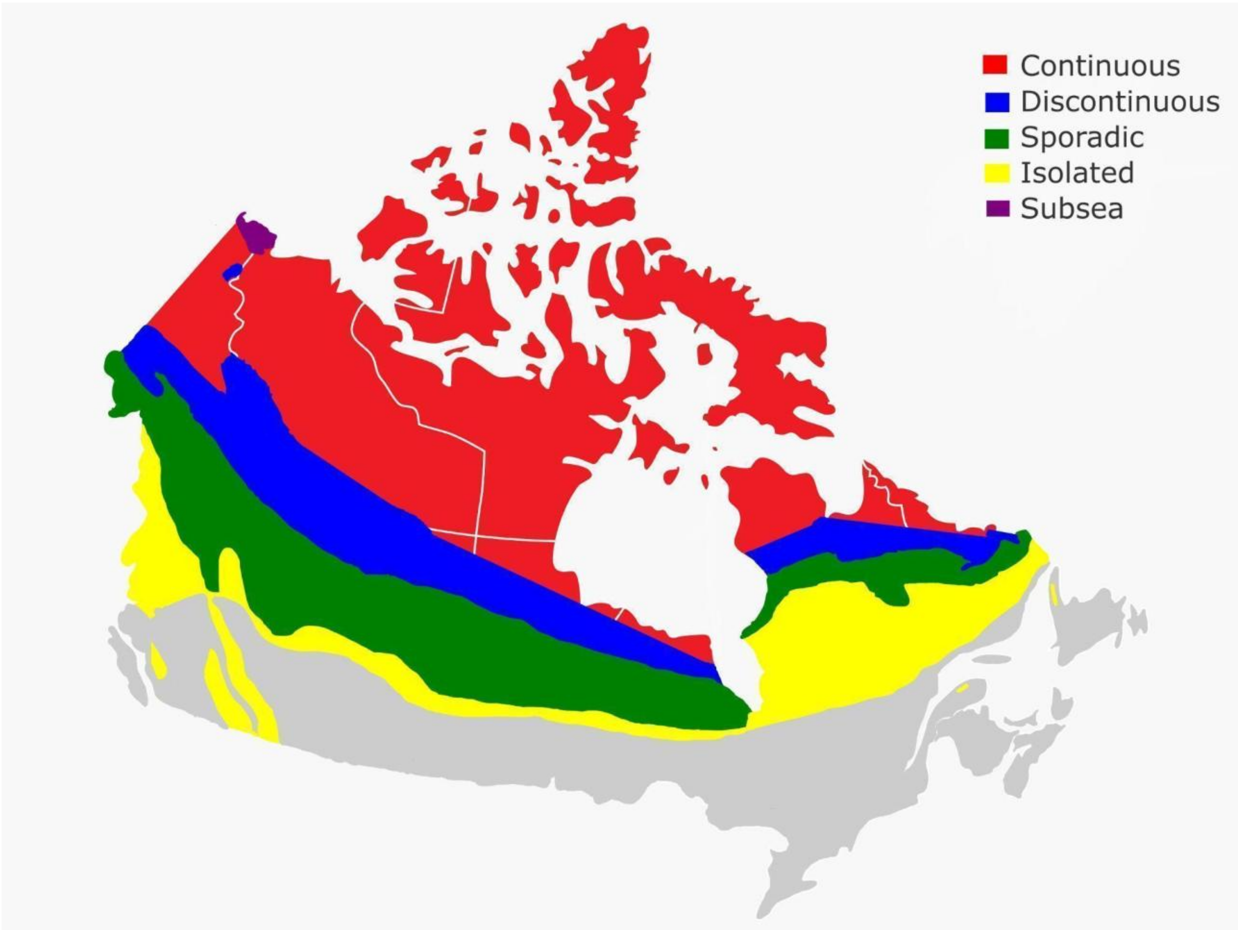

2nd year project report (2024-2025)

Numerical modelling of the permafrost thawing and its repercussions in the Northwest Territories

Aram Moradi and Vadim Kravchinsky *

Institute for Geophysical Research, Department of Physics, University of Alberta

March 2025

* Correspondence to vadim@ualberta.ca

Abstract

This study employs advanced machine learning (ML) techniques—Random Forest (RF) and Neural Networks (NNs)—to investigate permafrost thaw dynamics in the Northwest Territories, with a particular focus on the Mackenzie River Delta. Utilizing the largest and most comprehensive datasets in North America—10 years of observations from 79 sites—we predict two key indicators of permafrost stability: Mean Annual Ground Temperature (MAGT) and Active Layer Thickness (ALT). Our results demonstrate the effectiveness of ML models in accurately forecasting permafrost conditions, with NNs outperforming RF in terms of prediction accuracy. The root mean squared error (RMSE) values for MAGT predictions were 0.52 (RF) and 0.41 (NNs), with corresponding R^2 values of 0.71 and 0.82, respectively. For ALT, RMSE values were 0.33 (RF) and 0.25 (NNs), with R^2 values of 0.62 and 0.77. As a key outcome, we developed the first high-resolution ML-based MAGT map for the study area, supported by a corresponding standard deviation (SD) map derived from 100 model iterations to quantify spatial uncertainty. These maps capture regional variability and highlight zones most susceptible to permafrost degradation. Notably, we identified a clear north-to-south warming gradient, with southern permafrost areas—especially south of the tree line—being more vulnerable to thaw.

A major strength of our ML approach lies in its data-driven methodology: instead of relying on interpolation or extrapolation between observed points, ML derives spatial predictions based on learned relationships between input parameters across the entire study region. This enables more accurate, robust, and spatially continuous assessments of permafrost conditions. Future work will extend this methodology to generate a comparable high-resolution map for ALT, accompanied by its own uncertainty analysis. Additionally, we will refine model sensitivity and incorporate Representative Concentration Pathways (RCPs) to forecast how permafrost will respond to different climate change scenarios. These efforts aim to support targeted adaptation planning, infrastructure risk assessments, and broader strategies for managing Arctic landscape change under a warming climate.

1. Introduction

Climate change presents significant challenges, particularly in regions characterized by permafrost. Permafrost, defined as ground that remains frozen for at least two consecutive years, is a critical component of Earth's cryosphere, influencing Arctic landscapes, hydrological systems, and climate feedback mechanisms. It underpins the structural integrity of polar environments and sequesters substantial quantities of organic carbon within frozen soils. Its distribution, processes, and interactions with other environmental factors, such as glaciers, are influenced by climate and location, resulting in diverse manifestations that are challenging to categorize, particularly in the context of changing climates (Dobinski, 2011). Despite this seemingly straightforward definition, complexities arise from varying physical states, such as water-ice mixtures or dry conditions. Permafrost serves as a natural barrier regulating hydrology and ecosystems and locking away nearly twice the amount of carbon present in the atmosphere. However, rising global temperatures exacerbate its vulnerability to thaw, with profound implications for ecosystems, infrastructure, and climate systems, highlighting its significant role in regulating environmental stability (Kokelj et al., 2023; Jones et al., 2023).

Permafrost thaw has profound implications for global climate, ecosystems, and human infrastructure (Bouffard et al., 2021; Von Deimling et al., 2021; Smith et al., 2022). It releases significant quantities of greenhouse gases, including methane and carbon dioxide, forming a feedback loop that exacerbates global warming. Schaefer et al. (2014), Schuur et al. (2015), and Chadburn et al. (2017) emphasize the magnitude and irreversible nature of these emissions under various climate scenarios. Rising permafrost temperatures have been documented by Biskaborn et al. (2019), while Luo et al. (2016) reveal significant heterogeneity in active layer thickness (ALT) across the Northern Hemisphere, ranging from Arctic regions to mid-latitudes. Ecological shifts in vegetation and soil hydrology are detailed by Jin et al. (2021), and carbon vulnerability in thawing peatlands is examined by Treat et al. (2021). O'Neill et al. (2023) highlight spatial variability in permafrost thaw and subsidence in the Northwest Territories, while Jorgenson et al. (2010) explore factors influencing thaw progression. Further, studies by Orgogozo et al. (2019) and Nitzbon et al. (2020) highlight the role of hydrological and thermokarst-inducing processes, emphasizing the urgency of addressing permafrost degradation's cascading effects.

Advanced numerical models and machine learning (ML) approaches are transforming permafrost research. Qin et al. (2017) and Perreault et al. (2021) used numerical models like GIPL2 and cryohydrogeological frameworks to study the Active Layer Thickness (ALT) and permafrost thermal states under climate change, revealing significant degradation due to warming. The CryoGrid model (Westermann et al., 2022) and Arctic Terrestrial Simulator (Painter et al., 2016) exemplify advancements in simulating thermal, hydrological, and ecological processes, while Karra et al. (2014) integrate complex thermokarst dynamics. ML approaches enhance prediction capabilities, as shown by Ni et al. (2021) and Ran et al. (2022), who improved projections of Mean Annual Ground Temperature (MAGT) and ALT. Yin et al. (2021) assessed thermokarst landslide risks, while Li et al. (2023) applied Random Forest models for thaw settlement risk mapping. Chance et al. (2024) combined ML with atmospheric reanalysis data to achieve accurate soil temperature predictions. Collectively, these efforts highlight the importance of interdisciplinary research, integrating field observations, numerical simulations, and ML to address the impacts of permafrost thaw on ecosystems, infrastructure, and climate systems.

This study focuses on the Northwest Territories and employs machine learning and numerical modelling techniques to assess permafrost thaw dynamics and rates. ML models have advanced substantially in the last few years, enabling the analysis of complex environmental datasets with unprecedented efficiency and accuracy. This progress allows for more reliable forecasts and informed decision-making across various environmental applications (Rolnick et al., 2022). ML models are particularly effective in elucidating relationships between dependent variables and other explanatory variables (Wheeler et al., 2013).

In our approach, we combine ML models to simulate the permafrost dynamics, specifically focusing on MAGT and ALT. We are the first to employ a data-driven methodology using advanced machine learning techniques, including We are the first to employ a data-driven methodology using advanced machine learning techniques, including Random Forest (RF) and Neural Networks (NNs), applied to 79 observational sites across the Northwest Territories (Ensom et al., 2019). This dataset, spanning 10 years, represents one of the largest and longest observational records of permafrost conditions in North America to date. We anticipate that the unprecedented scale and resolution of our analysis will provide critical insights into permafrost thaw dynamics, offering globally relevant findings that extend beyond regional implications.

2. Goals and research questions

The three main goals of our project leverage the transformative potential of machine learning (ML) models to enhance permafrost research and thawing forecasting in the Northwest Territories, with a focus on the Mackenzie River Delta:

Goal 1: Evaluating the impact of permafrost thawing on regions with mud-drilling sumps and related infrastructures using machine learning (ML) approaches. This involves demonstrating how various environmental and climatic parameters can predict Mean Annual Ground Temperature (MAGT) and Active Layer Thickness (ALT), thereby identifying regions at high risk of permafrost thaw. This goal establishes a robust foundation for data-driven approaches to assess permafrost vulnerability.

Goal 2: Quantify permafrost thaw rates under different climate scenarios defined by Representative Concentration Pathways (RCPs), such as increased greenhouse gas emissions (RCP 8.5), mitigation efforts (RCP 2.6), etc. ML models will help identify key factors influencing permafrost thawing in the Mackenzie River Delta, ensuring accurate predictions relevant to current environmental challenges, such as infrastructure stability, ecosystem changes, and water resource management in the region.

Goal 3: Enhance the accuracy and reliability of ML-based predictions through sensitivity analysis and model calibration using one of the largest and longest observational permafrost datasets in North America. This goal addresses sources of uncertainty and refines projections critical for future permafrost thaw predictions.

To achieve these goals, we have addressed some of the research questions in our 2nd-year report:

1. What key parameters can be effectively used to predict MAGT and ALT? This question aims to identify the most influential environmental, climatic, and geographical variables driving permafrost dynamics. Understanding these parameters is crucial for constructing reliable predictive models and informing mitigation strategies.

2. How accurately can ML models, such as RF and NNs, predict regions at risk of permafrost thaw? By leveraging ML models, this question addresses the potential of advanced computational techniques to provide spatially explicit and accurate predictions, facilitating the early identification of vulnerable regions and enabling proactive planning.

3. Which regions in the Mackenzie Delta are most vulnerable to permafrost thaw based on ML predictions? This question focuses on spatial variability within the Mackenzie Delta, where environmental and climatic conditions may vary significantly. Identifying high-risk areas is essential for prioritizing adaptation efforts and safeguarding critical infrastructure.

3. Data and Methods

3.1. Data Sources

This study uses detailed ground temperature data collected from 79 sites, including sentinel, embankment, alignment and creek bank boreholes and type of terrain (hilltops, riparian zones, and peatlands) along the Inuvik to Tuktoyaktuk Highway (Fig. 1) from 2017 to 2023, these regions are underlain by continuous ice-rich permafrost with thickness varying from 100 m near Inuvik to over 500 m near Tuktoyaktuk (Ensom et al., 2019; Rudy et al., 2019). It records ground temperatures at various depths (0.2, 0.5, 1, 1.5, 2, 4, 7, 10, 20) in meters monthly to monitor the warmth patterns of the road embankments and the frozen ground underneath. Using this ground temperature, ALT can be extracted at the depth the temperature passes 0 in each site, and MAGT can be extracted by monitoring the depth at which fluctuations in temperature are minimal (normally more than 10 meters).

Additionally, we use the geological and geotechnical data in the same area, including soil composition (gravel, sand, silt, clay), moisture content, liquid water, soil organic carbon (SOC), dissolved organic carbon (DOC), slope, aspect, longitude, latitude, elevation, vegetation that transitions from open woodland around Sitidgi Lake in the south to low shrub tundra further north, culminating in tundra vegetation along the coast. Another dataset is climate data, including air temperature, precipitation, and snow ground for three large regions including Inuvik, Trail Valley and Tuktoyaktuk (Meteorological and Satellite Service of Canada data) Using air temperature, thawing degree days (TDD), and freezing degree days (FDD) can be calculated and added to climate data.

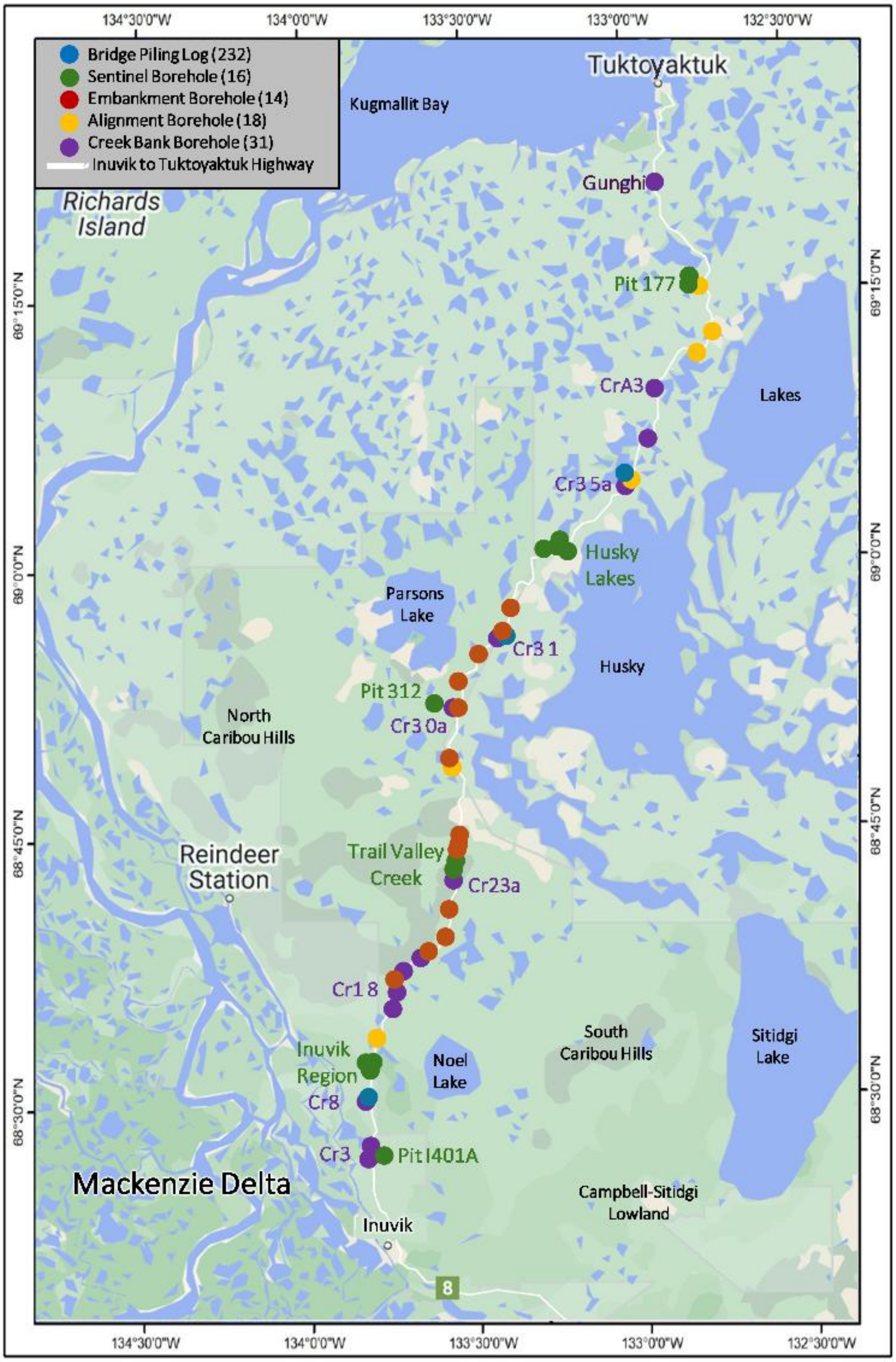

Figure 1. The location of the geotechnical boreholes with the field data in the Inuvik to Tuktoyaktuk Highway corridor. The figure was created using Google Maps, coordinates, and a site description from Ensom et al. (2019).

In our analysis, we prioritized mean annual ground temperature (MAGT) and active layer thickness (ALT) as key factors of the permafrost's thermal condition because of their important role in understanding permafrost dynamics that was demonstrated by Qin et al. (2017), Ran et al. (2022), Chance et al. (2024), Chang et al. (2024). It determines whether the ground remains frozen year-round or if thawing occurs. Changes in MAGT directly influence permafrost degradation or preservation (Daly et al., 2022). Warmer MAGT increases the likelihood of thawing, which can destabilize landscapes and release stored carbon (Dieleman et al., 2022; Swanson et al., 2021). This measures the thickness of the soil layer above permafrost that thaws and refreezes annually. ALT is crucial for understanding how deep seasonal thawing occurs, which impacts the hydrology, vegetation, and infrastructure in permafrost regions, as demonstrated by Hu et al. (2020), Garibaldi et al. (2022), and Ogden et al. (2023). A thicker ALT signals deeper thawing, which can lead to greater carbon release, surface subsidence, and other ecological consequences (Zhao et al., 2021; Ran et al., 2022).

3.2. Data processing and standardization

Data processing and standardization are critical steps in preparing datasets for analysis and ensuring the reliability of results. Our approach begins with addressing (i) missing, unnecessary, or inconsistent data to maintain dataset integrity and completeness. Missing data is handled using a combination of advanced techniques, including ML-based imputation, where models predict missing values based on existing patterns, and interpolation methods to estimate missing entries using trends within the data (Merchant & McBlane, 2024). These strategies ensure that the dataset remains robust and avoids biases introduced by incomplete information. (ii) Once cleaned, the data is standardized and converted into appropriate formats compatible with our analytical tools. This step includes transforming variables, normalizing scales, and organizing the data into a consistent structure to facilitate accurate calculations. (iii) We integrate multiple datasets and extract relevant features, such as thermal indices, hydrological parameters, and vegetation cover, which are key to modelling and analyzing permafrost thawing rates in 3 large regions. This integrated and well-prepared dataset enables the effective application of ML algorithms to uncover patterns and make precise predictions (Boike, 2021).

3.3. Methodology

3.3.1. Machine Learning

Different ML methods offer diverse approaches to data analysis and predictive modelling. NNs and RF are two highly effective techniques, each with distinct benefits and applications. This section outlines these approaches, their theoretical foundations, and their real-world applications within the framework of our investigation. Specifically, the RF algorithm was applied for regression tasks, analyzing how variations in MAGT and ALT influence permafrost thawing rates and identifying the most significant environmental factors. NNs were employed to explore complex, nonlinear interactions between variables, such as the relationship between geotechnical and climatic conditions and their combined effect on permafrost thawing (Cheysari et al., 2024).

We performed the following ML procedures:

- Model Training: The models were trained to predict MAGT and ALT using historical field data. Input variables included temperature, soil composition, moisture content, etc., while outputs represented the predicted MAGT and ALT. The training process used a supervised learning approach, fitting the model to understand patterns in the data and predict outcomes based on learned relationships (Sarker, 2021).
- Validation: Cross-validation techniques were employed to ensure generalizability and prevent overfitting. This involved partitioning the dataset into training and validation subsets, iteratively tuning model parameters, and assessing performance metrics such as correlation coefficient (R^2), which is the proportion of the variance in the observed data explained by the model, root mean squared error (RMSE) that is the square root of the average squared differences between predictions and observations, and bias that the average difference between predicted and observed values, showing systematic over or underestimation by the model on the validation data (Sarker, 2021).
- Testing: The models' predictive accuracy was evaluated on an independent testing dataset, distinct from the training and validation data. The same performance metrics as R^2, RMSE, and bias were used to quantify the models' ability to generalize to unseen data (Sarker, 2021).

The study employed two ML models, RF and NNs, to analyze how MAGT and ALT influence thawing rates and identify critical environmental factors that explored nonlinear relationships and interactions within the dataset. For example, the interaction might be between geographical location (latitude and longitude) and climatic conditions (temperature and precipitation) and how these parameters jointly influence permafrost thaw rates in a nonlinear manner. It is important to note that "future MAGT and ALT" refers to modelled projections based on climatic scenarios, not actual future data, as derived from RCPs.

3.3.2. Random Forest

RF is an ensemble machine learning algorithm that constructs a collection of decision trees to improve classification and regression accuracy. The fundamental concept behind RF is to combine the predictions of multiple decision trees to create a more robust and accurate model compared to a single tree predictor. Each tree in the forest is independently constructed using a random subset of the data and a random selection of features at each split. This technique promotes diversity among the trees and reduces the risk of overfitting (Breiman, 2001).

The RF algorithm operates by leveraging two sources of randomness: (1) bootstrap sampling, where the training dataset is resampled with replacement to create subsets for building individual trees, and (2) random feature selection, where a random subset of predictors is considered for splitting at each node. This randomness ensures that the decision trees in the forest are decorrelated, thereby improving the overall model's generalization ability (Kulkarni, 2013).

There are several advantages of RF:

1. **Generalization Error**: RF is highly robust against overfitting as the number of trees increases. The algorithm provides an internal estimate of the generalization error through out-of-bag (OOB) data—samples not included in the bootstrap datasets (Breiman, 2001).
2. **Variable Importance**: RF can measure the relative importance of each input feature, making it an excellent tool for feature selection and understanding variable influences (Breiman, 2001).
3. **Versatility**: The algorithm is effective for both classification and regression tasks and can handle high-dimensional datasets (Breiman, 2001).
4. **Robustness**: RF performs well even with missing data and are less sensitive to noise compared to other ensemble methods like boosting (Breiman, 2001).

In this study, we use RF regression to predict mean annual ground temperature (MAGT) and active layer thickness (ALT). The RF model integrates geotechnical, geological, and climatic variables, allowing for accurate predictions of MAGT and ALT under current conditions and their projected changes under future climate scenarios. Leveraging the algorithm's ability to model relationships and handle diverse datasets, the methodology is designed to evaluate how permafrost responds to environmental changes and identify key factors influencing permafrost thaw (Meloche et al., 2022).

The training phase involves building the RF model using historical field observations of MAGT and ALT, along with corresponding geotechnical and climatic features. Key input variables include soil thermal properties like moisture content (MC), snow ground (SG), thawing degree days (TDD), freezing degree days (FDD), air temperature (AT), precipitation (Pre), and topographic features like elevation (Ele), slope, and aspect. These features are selected based on their established influence on permafrost thermal dynamics. The effects of variables on MAGT and ALT, our models were designed using the following specifications (Ni et al., 2021):

$$\text{MAGT}=f_1(TDD)+f_2(FDD)+f_3(MC)+f_4(SG)f_5(Pre)+f_6(SOC)+f_7(Lon)+f_8(Lat)+f_9(Ele)$$
$$+f_{10}(DOC)+f_{11}(VEG)+f_{12}(Aspect)+f_{13}(Liq_{water})+f_{14}(Soil_{comp})+f_{15}(AT)+f_{16}(Slope) \quad \textbf{(1)}$$

$$\text{ALT}=f_1(TDD)+f_2(FDD)+f_3(MC)+f_4(SG)f_5(Pre)+f_6(SOC)+f_7(Lon)+f_8(Lat)+f_9(Ele)$$
$$+f_{10}(DOC)+f_{11}(VEG)+f_{12}(Aspect)+f_{13}(Liq_{water})+f_{14}(Soil_{comp})+f_{15}(AT)+f_{16}(Slope) \quad \textbf{(2)}$$

Bootstrap sampling is applied to create training subsets, and the model iteratively learns the relationships between the predictors and target variables. During training, the RF algorithm evaluates multiple decision trees, each considering a random subset of features at each split, ensuring model robustness and minimizing overfitting.

To simulate future conditions, climate scenarios such as Representative Concentration Pathways (RCPs) are incorporated. For example, RCP2.6 (low emissions), RCP4.5 (moderate emissions), RCP6.0 (intermediate emissions), and RCP8.5 (high emissions) provide projections of air temperature, precipitation, and other climate variables. These projections are used as inputs to predict future MAGT and ALT distributions. By simulating these scenarios, the model evaluates the potential impacts of warming trends on permafrost stability, highlighting regions at risk of thawing (Zhang et al., 2024).

The RF model is validated using cross-validation techniques, which partition the dataset into training and validation subsets. This approach ensures the model generalizes well to unseen data and avoids overfitting. Performance metrics such as RMSE, R^2, and bias are used to assess the model's accuracy on the validation dataset. Out-of-bag (OOB) error estimates, calculated from samples not included in bootstrap subsets, provide an additional measure of the model's predictive performance (Park et al., 2019).

For testing, an independent dataset of observed MAGT and ALT values is reserved. This dataset is not used during training or validation and serves to evaluate the model's predictive accuracy in real-world conditions. Comparisons between observed and predicted MAGT and ALT values allow for rigorous assessment of model performance.

By combining current and projected data, the RF model facilitates a comprehensive understanding of permafrost dynamics under various environmental conditions. It also identifies critical factors influencing permafrost thaw, such as snow insulation, soil thermal properties, and climate variability. This methodology offers a reliable framework for predicting permafrost responses to climate change and informing adaptation strategies in vulnerable regions (Baral & Haq, 2020).

3.3.3. Neural Networks

NNs are powerful machine learning models designed to handle complex nonlinear prediction tasks, making them well-suited for analyzing permafrost dynamics. Their adaptability enables the modelling of nonlinear data relationships across various domains, including time series analysis and environmental studies. NNs offer a flexible architecture that can be tailored to specific data features through various configurations, such as feedforward, convolutional, and recurrent networks. NNs excel at capturing intricate relationships within data that might be overlooked by simpler models. They are composed of layers of interconnected nodes, where each node represents a specific feature or input variable. The network learns from data by adjusting the weights of these connections through a process called backpropagation, which minimizes the loss or cost function associated with the predictions. This iterative optimization ensures that the network progressively improves its ability to predict outcomes accurately (Ma et al., 2021).

NNs have proven to be a powerful tool for modelling complex, nonlinear relationships inherent in permafrost systems. Their flexibility allows for the incorporation of diverse environmental, geotechnical, and climatic data to predict key permafrost parameters, such as mean annual MAGT and ALT. NNs can also simulate how these parameters respond under different climate scenarios, providing critical insights into the dynamics of permafrost thaw (Liu et al., 2022).

In our study, NNs are employed to predict MAGT and ALT based on geotechnical, geological, and climatic datasets. The model architecture consists of multiple interconnected layers: an input layer that processes different properties, including soil thermal properties, snow depth, TDD, and topography; hidden layers that capture complex nonlinear interactions; and an output layer that predicts MAGT and ALT values. The training process adjusts the weights of these connections using backpropagation, minimizing a defined loss function to improve prediction accuracy. To account for future climate conditions, the model incorporates projections from RCPs such as RCP2.6, RCP4.5, RCP6 and RCP8.5. These scenarios provide input variables like air temperature, precipitation, and radiation to simulate changes in MAGT and ALT under different warming trajectories. By analyzing these scenarios, the NNs predict permafrost responses to projected climate variations, offering insights into thawing trends and identifying regions at risk of degradation (Thaler et al., 2023).

There are some advantages of NNs:

1. **Nonlinear Modelling:** NNs effectively model the intricate relationships among environmental variables influencing permafrost (Cai et al., 2024).
2. **Scalability:** The architecture can be adapted to accommodate large and diverse datasets from remote sensing and in situ measurements (Zhang et al., 2021).
3. **Feature Integration:** Neural networks (NNs) combine geospatial, climatic, and geotechnical variables for comprehensive modelling of permafrost dynamics (Baral & Haq, 2020).
4. **Temporal Analysis:** Different architectures are particularly adept at capturing temporal dependencies, which is essential for predicting seasonal and interannual changes (Glinskikh et al., 2024).

This methodology not only enhances our understanding of permafrost behaviour but also provides a robust framework for assessing the impacts of climate change on permafrost regions, aiding in adaptation and mitigation strategies.

4. Results

In the first two years of this study, our primary focus has been on adapting, testing, and implementing ML approaches while developing MATLAB and Python codes to process and refine available data. Last year, we began by analyzing ground temperature data from pit 312. In comparison to our first report, where ground temperature data was available only at depths of 1, 2, 4, 7, and 10 meters and was insufficient for comprehensive analysis. We identified the active layer as being less than 2 m, and therefore, we needed to examine the data for depths less than 2 m as well. We have now gathered extensive data over a 10-year period, including ground temperature measurements at shallower depths of 0.2, 0.5, 1, and 1.5 meters. This has allowed us to accurately determine the exact scope of ALT in this pit. In this dataset, the temperature at the deepest depth above 0°C is 1.5 m. The next measured depth, at 2 m, represents the onset of permafrost. Since there is no data between 1.5 and 2 m, this interval is considered a transition zone between ALT and permafrost.

4.1. Reliability Assessment of MAGT and ALT

In our first report, we used four parameters across 16 sites to generate synthetic data for predicting MAGT at additional locations. In the second year, we expanded our analysis by incorporating real data and utilizing 16 parameters across 79 sites to predict both MAGT and ALT. To evaluate the feasibility of these predictions, we employed RF and NNs, leveraging all available geotechnical, geological, and climate data from the study sites, with MAGT and ALT selected as key factors for assessing permafrost dynamics. Model predictions were compared with observed MAGT and ALT data, and performance was assessed using RMSE, Bias, and R^2, as presented in Figs. 2 and 3.

In Fig. 2, the black line represents the ideal 1:1 match between predicted and observed MAGT values, while the red dashed lines indicate the RMSE boundaries. Accurate predictions align closely with the black line. The RMSE values of 0.52 (RF) and 0.41 (NNs) demonstrate that the predicted MAGT values are close to the actual values, with RMSE values below 1 indicating high accuracy. The R^2 values of 0.71 (RF) and 0.82 (NNs) further highlight strong correlations between predicted and observed data. Minimal bias is observed, with RF underestimating MAGT by 0.03°C and NNs overestimating it by 0.07°C, indicating no significant systematic errors. These results highlight the effectiveness of both models in predicting MAGT, with NNs providing more precise predictions.

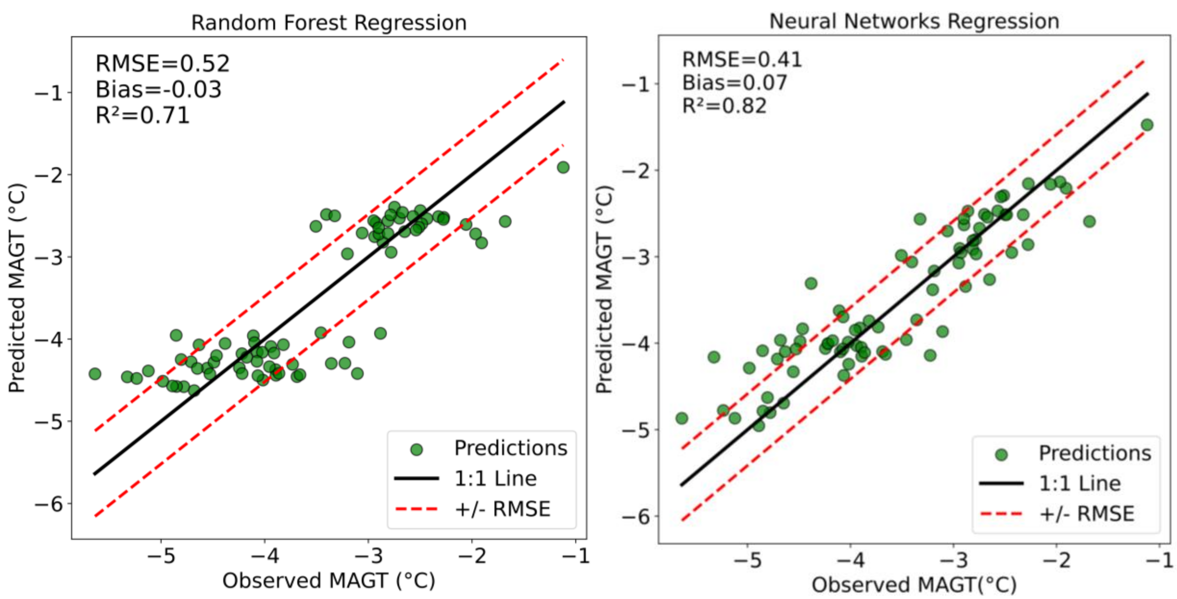

Figure 2. Observed versus predicted MAGT using RF and NNs models. The black line represents the ideal 1:1 match between predicted and actual values, while the red dashed lines delineate the RMSE boundaries. The values that are closer to the black line indicate better agreement between predicted and observed values.

Fig. 3 presents the relationship between observed ALT and predicted values derived from RF and NNs models. The RMSE values for ALT predictions are 0.33 (RF) and 0.25 (NNs), suggesting similarly high accuracy. The corresponding R^2 values of 0.62 (RF) and 0.77 (NNs) indicate that both models capture the variability of ALT well. Bias values reveal a slight overestimation by 0.02 m (RF) and an underestimation of 0.08 m (NNs). Like MAGT, ALT predictions exhibit no substantial systematic errors.

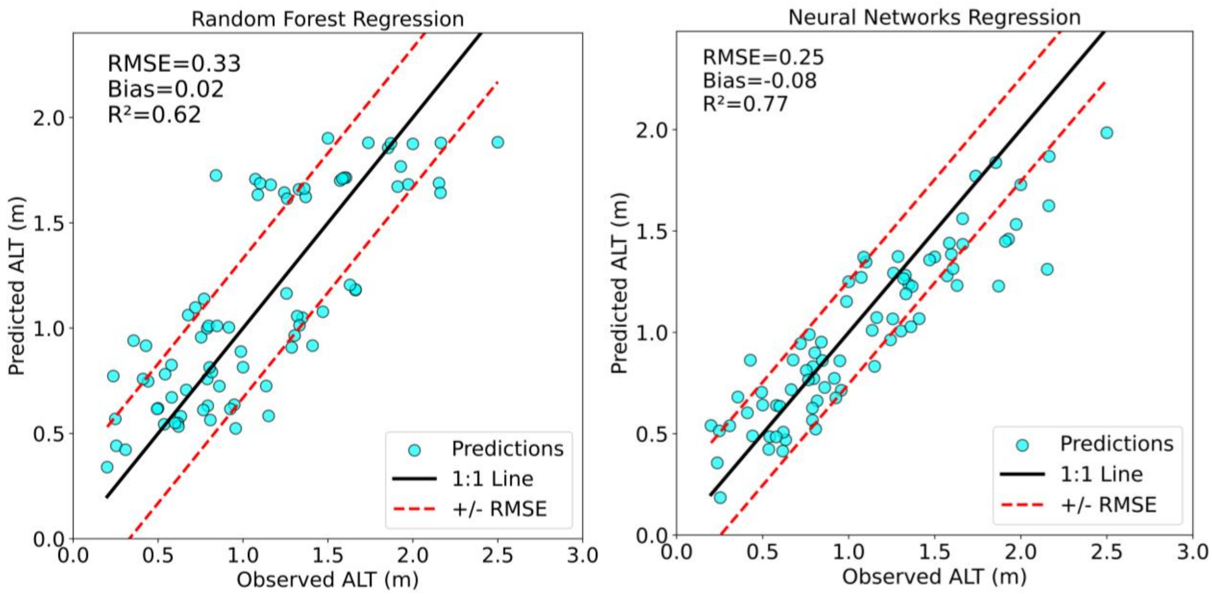

Figure 3. Observed versus predicted ALT using RF and NNs models. The solid black line marks the ideal 1:1 match between predicted and actual values, while the red dashed lines indicate RMSE boundaries. These results demonstrate that while both models perform adequately, NNs offer greater accuracy in predicting ALT.

Overall, both RF and NNs performed well, with NNs consistently achieving higher R^2 and lower RMSE values for both MAGT and ALT. This can be attributed to NNs' ability to capture complex relationships between input parameters and target variables, particularly for MAGT, where some features exhibit more linear behaviour compared to the non-linear dynamics of ALT. Additionally, MAGT reflects a large-scale, stable thermal state averaged over the year, while ALT is subject to seasonal fluctuations and is, therefore, more prone to noise, making its accurate prediction inherently more challenging.

For large time-scale variables like MAGT, even small errors in predictions can result in relatively high RMSE values due to the broader range of data. In contrast, short-time-scale ALT naturally has smaller errors, leading to lower RMSE values. The slight over- and underestimation in bias for both MAGT and ALT demonstrates the influence of local environmental conditions and highlights the need for sensitivity analyses to further refine the models. The sensitivity analysis is planned to be the next step of our project.

To evaluate regional performance and account for variations due to local environmental factors, we analyzed the RMSE and Bias values for three major regions separately: Tuktoyaktuk, Trail Valley, and Inuvik, as shown in Tables 1 and 2. Despite strong performance overall, NNs exhibited better results across the entire study area, particularly for Tuktoyaktuk and Inuvik.

Table1. Model error statistics of the ALT in different typical regions using RF & NNs.

Region		***Tuktoyaktuk***	***Trail Valley***	***Inuvik***	***Entire***
RF	**RMSE (m)**	0.33	0.30	0.34	0.33
	Bias (m)	0.04	-0.009	0.005	0.02
NNs	**RMSE (m)**	0.28	0.17	0.24	0.25
	Bias (m)	-0.1	-0.06	-0.08	-0.08

Table2. Model error statistics of the MAGT in different typical regions using RF & NNs.

Region		***Tuktoyaktuk***	***Trail Valley***	***Inuvik***	***Entire***
RF	**RMSE (°C)**	0.56	0.59	0.43	0.52
	Bias (°C)	0.06	-0.1	0.1	-0.03
NNs	**RMSE (°C)**	0.43	0.56	0.40	0.41
	Bias (°C)	0.06	0.08	0.07	0.07

For Inuvik and Tuktoyaktuk, the RMSE values for both MAGT and ALT are relatively uniform when compared to the entire region. However, in Trail Valley, NNs exhibited higher RMSE values for both MAGT and ALT compared to the other regions, likely due to the limited number of observation sites (11 sites), which impacts the model's generalization ability. In this region, RF demonstrated better predictive performance.

In regions with more observation sites, such as Inuvik (22 sites) and Tuktoyaktuk (46 sites), RF and NNs performed comparably, though NNs generally yielded better results. The higher RMSE for MAGT compared to ALT in these regions can be attributed to the greater sensitivity of MAGT to greenhouse gas effects and human activity, such as infrastructure development and deforestation, which usually alter thermal dynamics.

Regarding bias, RF tends to be more sensitive to local data, while NNs generalize better across regions. In Trail Valley and Inuvik, the higher bias observed in RF may indicate the presence of a transition zone between permafrost and seasonally frozen ground, suggesting abrupt thawing in these areas. Conversely, lower bias reflects more gradual thawing processes. These variations emphasize the complex nature of thaw dynamics and underscore the importance of understanding both local and regional influences on permafrost behaviour.

4.2. Spatial distribution of MAGT

Using geographical and climate data at additional sites in the Mackenzie Delta, MAGT was predicted to illustrate the permafrost distribution and assess the risk of thawing (Fig. 4).

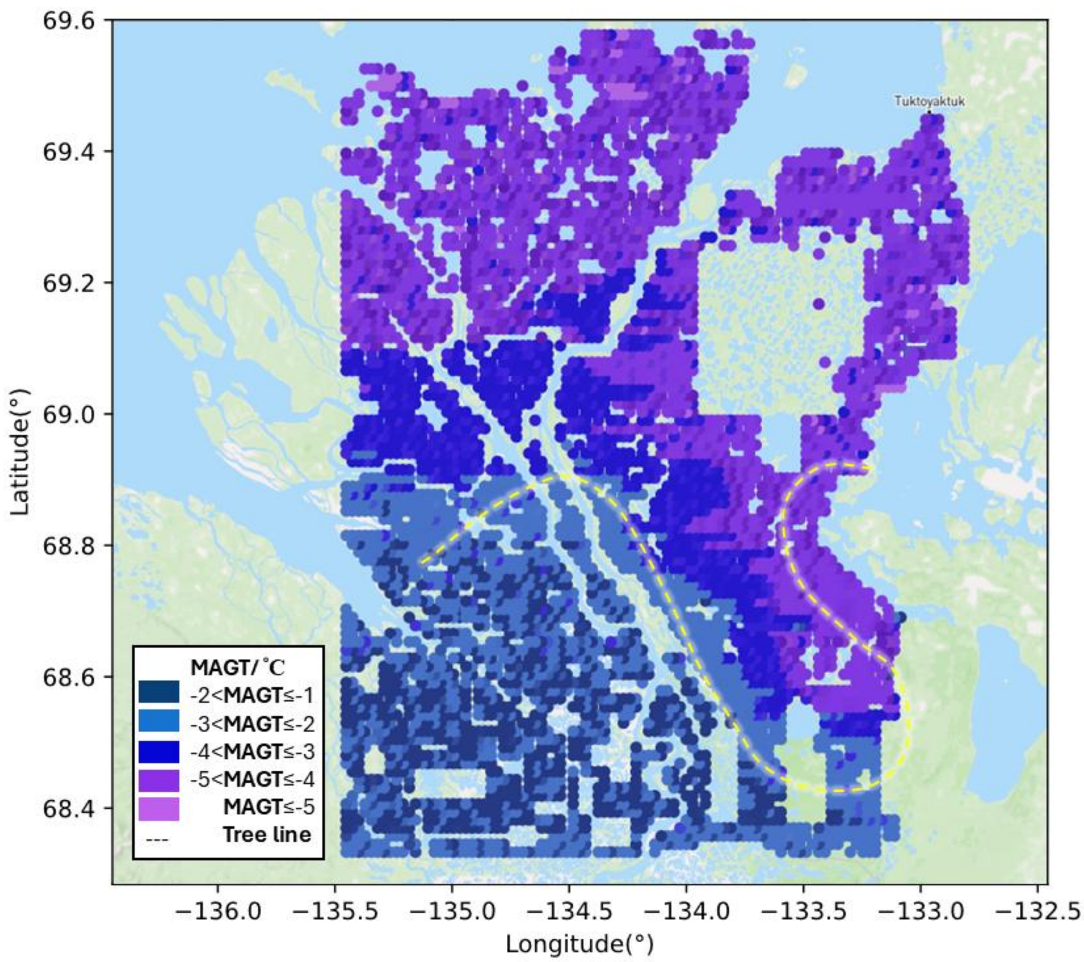

Figure 4. MAGT distribution, showing permafrost stability influenced by vegetation, water bodies, and climate. The yellow dashed line indicates the tree line limit.

The MAGT distribution is influenced by sparse vegetation, water bodies, and terrain variations, which affect permafrost stability. North of the tree line and central regions (-4°C to -5°C and below), limited tundra vegetation provides sparse vegetation and offers less insulation, contributing to colder ground temperatures in winter. South of the tree line (where MAGT ranges from approximately -1°C to -4°C), boreal forest and denser vegetation provide moderate insulation, which can reduce winter heat loss but also enhance summer warming due to shading and lower surface albedo. Water bodies, such as lakes and coastal zones, contribute to localized warming by storing and releasing heat. These landscape features create a clear north-to-south warming gradient, where southern permafrost is more vulnerable to thaw, while northern regions remain stable but could still be affected by climate change.

One significant advantage of this machine learning-based mapping approach is that it relies entirely on observational data and derived relationships among environmental variables, rather than on theoretical or physically parameterized models alone. Unlike conventional methods that rely on spatial interpolation or extrapolation between known data points, ML techniques calculate values at additional locations using learned patterns from a wide array of input parameters—such as vegetation cover, soil type, snow depth, and climate data—across the entire study area. This enables more accurate and spatially coherent predictions, even in areas without direct observations. The resulting maps capture real-world permafrost conditions with high spatial resolution, making them a powerful tool for analyzing regional trends and identifying zones of accelerated degradation. Furthermore, by integrating both ground-based measurements and remote sensing data, this approach allows for continuous model improvement and validation. High-resolution MAGT maps are particularly valuable for climate adaptation strategies, as they support targeted infrastructure planning, environmental monitoring, and proactive risk mitigation in vulnerable Arctic regions.

To create a map of standard deviation (SD) for MAGT in permafrost regions, 100 iterations were used in the calculation of SD to account for spatial and temporal variability in the data. Each iteration represents a prediction or sampling of the dataset, incorporating potential uncertainties such as measurement errors, interpolation artifacts, or environmental heterogeneity (e.g., variations in snow cover, vegetation, or soil properties). By repeating the calculation 100 times, the resulting SD map reflects a robust estimate of variability, ensuring that the final values are statistically reliable and capture the true range of temperature fluctuations across the study area. This approach is particularly important in permafrost regions, where ground temperatures are highly sensitive to local conditions, and understanding spatial variability is critical for predicting permafrost stability and its response to climate change (Fig. 5).

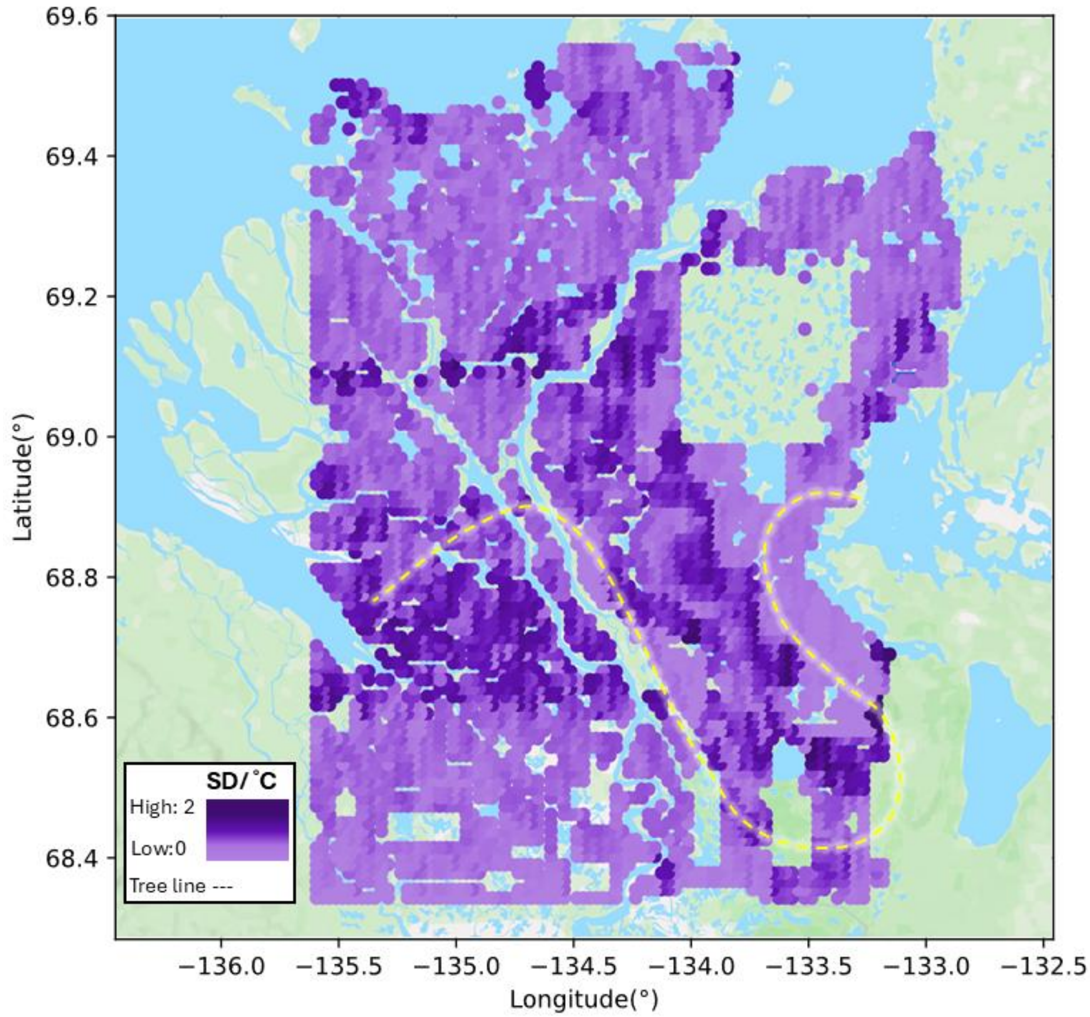

Figure 5. SD of MAGT from 100 iterations. The SD map reflects a robust estimate of variability, ensuring that the final values are statistically reliable and capture the true range of temperature fluctuations across the study area.

The SD map of MAGT logically reflects prediction uncertainty, with higher SD values occurring in transition zones where MAGT shifts significantly due to changes in environmental factors such as topography, snow cover, or vegetation. In contrast, more homogeneous regions, where MAGT remains stable, exhibit relatively constant SD values, indicating greater model certainty (below 1°C). The absence of strong SD variations in most coastal areas is reasonable, as temperature changes are often gradual due to the moderating influence of water bodies; however, localized high SD spots arise from complex coastal interactions, like varying ice cover (approximately 1.6°C). Additionally, SD is influenced by land cover types; areas with dense vegetation (e.g., shrubs, forests) could exhibit higher SD due to the insulating effects of organic layers and snow, while sparse vegetation shows lower SD due to more stable thermal properties (between 0.2°C and 0.5°C). Similarly, wetlands or tundra regions with variable moisture content and permafrost degradation could contribute to increased SD in certain areas. Overall, the SD distribution aligns well with spatial patterns, highlighting the interplay between environmental heterogeneity and ground thermal variability in permafrost regions.

5. Future work

The next critical step in this research is to complete the analysis of key input parameters to generate high-resolution maps of Active Layer Thickness (ALT) across the entire Inuvik–Tuktoyaktuk corridor and the Mackenzie Delta. This expansion will allow for a spatially continuous assessment of permafrost stability and better identification of areas most vulnerable to thawing. Completing the ALT mapping will complement the existing MAGT models and provide a more holistic understanding of permafrost dynamics throughout the study region. A central component of the ongoing work involves the refinement of ML models through comprehensive sensitivity analysis. This will help isolate and quantify the influence of individual input variables—such as air temperature, soil type, snow cover duration, vegetation density, and moisture content—on MAGT and ALT. Feature importance analysis will play a key role in prioritizing which environmental factors contribute most significantly to model predictions and which regions may be more sensitive to specific changes in these variables.

To enhance model precision, we will also focus on hyperparameter optimization—for example, adjusting the number of trees in the Random Forest algorithm or tuning the structure and activation functions within Neural Networks. These refinements are expected to improve both computational efficiency and predictive accuracy. Furthermore, conducting regional sensitivity mapping will help assess how the relationship between input variables and permafrost characteristics varies across distinct ecological and geological zones, enabling the development of more robust and site-specific models.

Future studies will also integrate a wider range of datasets, incorporating new ground measurements, remote sensing products, and climate reanalysis data to improve prediction accuracy and regional applicability. This expanded dataset will improve generalizability and allow for cross-validation in regions beyond the original training zones. Importantly, uncertainty quantification will be systematically integrated, particularly through ensemble modelling and probabilistic outputs from Neural Networks, to assess confidence levels in predictions and guide their use in decision-making contexts.

Given the increasing impacts of climate change on permafrost, future studies will integrate RCPs into predictive models. These scenarios (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) represent different levels of greenhouse gas emissions and their corresponding effects on global temperatures. By applying these projections, researchers will estimate future changes in MAGT and ALT, enabling the assessment of permafrost degradation under different climate trajectories. This will include scenario-based risk assessments, evaluating the extent of permafrost thaw-related hazards such as ground subsidence, infrastructure damage, carbon release and sumps. Additionally, spatial and temporal variability in permafrost response under different RCPs will be analyzed to understand how permafrost dynamics evolve over time. Ultimately, the integration of data-driven modelling, environmental sensitivity analysis, and climate scenario projections will strengthen our capacity to anticipate and manage the multifaceted impacts of permafrost thaw across northern landscapes.

Acknowledgments

We would like to acknowledge the support of the Government of the Northwest Territories and the University of Alberta. We also thank T. Ensom and S. Kokelj for providing the data and discussions at the project's initial stage.

References

Baral, P., & Haq, M. A. (2020). Spatial prediction of permafrost occurrence in Sikkim Himalayas using logistic regression, random forests, support vector machines and neural networks. *Geomorphology*, *371*, 107331.

Biskaborn, B. K., Smith, S. L., Noetzli, J., Matthes, H., Vieira, G., Streletskiy, D. A., ... & Lantuit, H. (2019). Permafrost is warming at a global scale. *Nature communications*, *10*(1), 264.

Boike, J., Chadburn, S., Martin, J., Zwieback, S., Althuizen, I. H., Anselm, N., ... & Wilcox, E. J. (2021). Standardized monitoring of permafrost thaw: a user-friendly, multiparameter protocol. *Arctic Science*, *8*(1), 153-182.

Bouffard, T. J., Uryupova, E., Dodds, K., Romanovsky, V. E., Bennett, A. P., & Streletskiy, D. (2021). Scientific cooperation: Supporting circumpolar permafrost monitoring and data sharing. *Land*, *10*(6), 590.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.

Cai, H., Wang, C., Ma, Z., Meng, F., Lin, Z., Ren, J., & Li, S. (2024). Predicting frost heave in soil-water systems using the generalized regression neural network optimized with particle swarm optimization algorithm. *Cold Regions Science and Technology*, *226*, 104291.

Chadburn, S. E., Burke, E. J., Cox, P. M., Friedlingstein, P., Hugelius, G., & Westermann, S. (2017). An observation-based constraint on permafrost loss as a function of global warming. *Nature climate change*, *7*(5), 340-344.

Chance, R., Ahajjam, A., Putkonen, J., & Pasch, T. (2024). Artificial intelligence for predicting arctic permafrost and active layer temperatures along the Alaskan North Slope. *Earth Science Informatics*, 1-19.

Chang, T., Yi, Y., Jiang, H., Li, R., Lu, P., Liu, L., ... & Zhao, J. (2024). Unraveling the non-linear relationship between seasonal deformation and permafrost active layer thickness. *npj Climate and Atmospheric Science*, *7*(1), 308.

Daly, S. V., Bonnaventure, P. P., & Kochtitzky, W. (2022). Influence of ecosystem and disturbance on near-surface permafrost distribution, Whatì, Northwest Territories, Canada. *Permafrost and Periglacial Processes*, *33*(4), 339-352.

Dieleman, C. M., Day, N. J., Holloway, J. E., Baltzer, J., Douglas, T. A., & Turetsky, M. R. (2022). Carbon and nitrogen cycling dynamics following permafrost thaw in the Northwest Territories, Canada. *Science of the Total Environment*, *845*, 157288.

Dobinski, W. (2011). Permafrost. *Earth-Science Reviews*, *108*(3-4), 158-169.

Ensom, T., Morse, P. D., Kokelj, S. V., MacDonald, E., Young, J., Tank, S., Subedi, R., Grozic, E., & Castagner, A. (2019). Permafrost Geotechnical Borehole Data Synthesis: Inuvik-Tuktoyaktuk Region, Northwest Territories. *Geological survey of Canada, Open File,* 8652, 78. Government of Canada. https://doi.org/10.4095/321869

Fatolahzadeh Gheysari, A., & Maghoul, P. (2024). A framework to assess permafrost thaw threat for land transportation infrastructure in northern Canada. *Communications Earth & Environment*, *5*(1), 167.

Garibaldi, M. C., Bonnaventure, P. P., Smith, S. L., & Duchesne, C. (2022). Active layer variability and change in the Mackenzie Valley, Northwest Territories between 1991-2014: An ecoregional assessment. *Arctic, Antarctic, and Alpine Research*, *54*(1), 274-293.

Glinskikh, V., Nechaev, O., Mikhaylov, I., Nikitenko, M., & Danilovskiy, K. (2024). Transient Electromagnetic Monitoring of Permafrost: mathematical Modeling Based on Sumudu Integral Transformand Artificial Neural Networks.

He, J., Yang, K., Tang, W., Lu, H., Qin, J., Chen, Y., & Li, X. (2020). The first high-resolution meteorological forcing dataset for land process studies over China. *Scientific data*, *7*(1), 25.

Jin, X. Y., Jin, H. J., Iwahana, G., Marchenko, S. S., Luo, D. L., Li, X. Y., & Liang, S. H. (2021). Impacts of climate-induced permafrost degradation on vegetation: A review. *Advances in Climate Change Research*, *12*(1), 29-47.

Jones, M. C., Grosse, G., Treat, C., Turetsky, M., Anthony, K. W., & Brosius, L. (2023). Past permafrost dynamics can inform future permafrost carbon-climate feedbacks. Communications Earth & Environment, 4(1), 272.

Jorgenson, M. T., Romanovsky, V., Harden, J., Shur, Y., O'Donnell, J., Schuur, E. A., ... & Marchenko, S. (2010). Resilience and vulnerability of permafrost to climate change. *Canadian Journal of Forest Research*, *40*(7), 1219-1236.

Jorgenson, M. T., & Grosse, G. (2016). Remote sensing of landscape change in permafrost regions. *Permafrost and periglacial processes*, *27*(4), 324-338.

Karra, S., Painter, S. L., & Lichtner, P. C. (2014). Three-phase numerical model for subsurface hydrology in permafrost-affected regions (PFLOTRAN-ICE v1. 0). *The Cryosphere*, *8*(5), 1935-1950.

Kokelj, S. V., Gingras-Hill, T., Daly, S. V., Morse, P. D., Wolfe, S. A., Rudy, A. C., ... & Young, J. M. (2023). The Northwest Territories Thermokarst Mapping Collective: A northern-driven mapping collaborative toward understanding the effects of permafrost thaw. *Arctic Science*, *9*(4), 886-918.

Kulkarni, V. Y., & Sinha, P. K. (2012, July). Pruning of random forest classifiers: A survey and future directions. In *2012 International Conference on Data Science & Engineering (ICDSE)* (pp. 64-68). IEEE.

Leverington, D. W., & Duguay, C. R. (1997). A neural network method to determine the presence or absence of permafrost near Mayo, Yukon Territory, Canada. *Permafrost and Periglacial Processes*, *8*(2), 205-215.

Li, R., Zhang, M., Pei, W., Melnikov, A., Zhang, Z., & Li, G. (2023). Risk evaluation of thaw settlement using machine learning models for the Wudaoliang-Tuotuohe region, Qinghai-Tibet Plateau. *Catena*, *220*, 106700.

Liu, Q., Niu, J., Lu, P., Dong, F., Zhou, F., Meng, X., Xu, W., Li, S., & Hu, B.X. (2022). Interannual and seasonal variations of permafrost thaw depth on the Qinghai-Tibetan plateau: A comparative study using long short-term memory, convolutional neural networks, and random forest. *Science of The Total Environment*, *838*, 155886.

Luo, D., Wu, Q., Jin, H., Marchenko, S. S., Lü, L., & Gao, S. (2016). Recent changes in the active layer thickness across the northern hemisphere. *Environmental Earth Sciences*, *75*, 1-15.

Ma, Z., Liu, Z., Pu, J., Xu, L., Li, K., Wangqu, L., Wu, R., Ma, Y., Chen, Y., & Duguay, C. (2021). Deep convolutional neural network with random field model for lake ice mapping from Sentinel-1 imagery. *International Journal of Remote Sensing*, 42(24), 9351-9375.

Meloche, J., Langlois, A., Rutter, N., McLennan, D., Royer, A., Billecocq, P., & Ponomarenko, S. (2022). High-resolution snow depth prediction using random forest algorithm with topographic parameters: A case study in the Greiner watershed, Nunavut. *Hydrological Processes*, *36*(3), p.e14546.

Merchant, M. A., & McBlane, L. (2024). Machine Learning-Based Active Layer Thickness Estimation over Permafrost Landscapes by Upscaling Airborne Remote Sensing Measurements with Cloud-Computing Geotechnologies.

Nitzbon, J., Westermann, S., Langer, M., Martin, L. C. P., Strauss, J., Laboor, S., & Boike, J. (2020). *Fast response of cold ice-rich permafrost in northeast Siberia to a warming climate Nature Commununications, 11, 2201*.

Ni, J., Wu, T., Zhu, X., Hu, G., Zou, D., Wu, X., Li, R., Xie, C., Qiao, Y., Pang, Q., & Hao, J. (2021). Simulation of the present and future projection of permafrost on the Qinghai-Tibet Plateau with statistical and machine learning models. *Journal of Geophysical Research: Atmospheres*, *126*(2), e2020JD033402.

Ogden, E. L., Cumming, S. G., Smith, S. L., Turetsky, M. R., & Baltzer, J. L. (2023). Permafrost thaw induces short-term increase in vegetation productivity in northwestern Canada. *Global Change Biology*, *29*(18), 5352-5366.

O'Neill, H. B., Smith, S. L., Burn, C. R., Duchesne, C., & Zhang, Y. (2023). Widespread permafrost degradation and thaw subsidence in Northwest Canada. *Journal of Geophysical Research: Earth Surface*, *128*(8), e2023JF007262.

Orgogozo, L., Prokushkin, A. S., Pokrovsky, O. S., Grenier, C., Quintard, M., Viers, J., & Audry, S. (2019). Water and energy transfer modeling in a permafrost-dominated, forested catchment of Central Siberia: The key role of rooting depth. *Permafrost and Periglacial Processes*, *30*(2), 75-89.

Painter, S. L., Coon, E. T., Atchley, A. L., Berndt, M., Garimella, R., Moulton, J. D., ... & Wilson, C. J. (2016). Integrated surface/subsurface permafrost thermal hydrology: Model formulation and proof-of-concept simulations. *Water Resources Research*, *52*(8), 6062-6077.

Park, H., Kim, K., & Lee, D. K. (2019). Prediction of severe drought area based on random forest: Using satellite image and topography data. *Water*, *11*(4), 705.

Perreault, J., Fortier, R., & Molson, J. W. (2021). Numerical modelling of permafrost dynamics under climate change and evolving ground surface conditions: application to an instrumented permafrost mound at Umiujaq, Nunavik (Québec), Canada. *Écoscience*, *28*(3-4), 377-397.

Qin, Y., Wu, T., Zhao, L., Wu, X., Li, R., Xie, C., Pang, Q., Hu, G., Qiao, Y., Zhao, G., Liu, G., Zhu, X., & Hao, J. (2017). Numerical modeling of the active layer thickness and permafrost thermal state across Qinghai-Tibetan Plateau. *Journal of Geophysical Research: Atmospheres*, *122*(21), 11-604.

Ran, Y., Li, X., Cheng, G., Che, J., Aalto, J., Karjalainen, O., Hjort, J., Luoto, M., Jin, H., Obu, J., Hori, M., Yu, Q., & Chang, X. (2022). New high-resolution estimates of the permafrost thermal state and hydrothermal conditions over the Northern Hemisphere. *Earth system science data*, *14*(2), 865-884.

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Dupont, N. M., Jaques, N., Brown, A. W., Luccioni, A., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C., Ng, A. Y., Hassabis, D., Platt, J. C., Creutzig, F., Chayes, J., & Bengio, Y. (2022). Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55(2), 1-96.

Rudy, A. C. A., Kokelj, S. V., Morse, P. D., & Ensom, T. (2019) ReportPermafrost Ground Temperature Report: Inuvik to Tuktoyaktuk Highway Sentinel sites, Northwest Territories.

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *Springer Nature computer science*, *2*(3), 160.

Schaefer, K., Lantuit, H., Romanovsky, V. E., Schuur, E. A., & Witt, R. (2014). The impact of the permafrost carbon feedback on global climate. *Environmental Research Letters*, *9*(8), 085003.

Schneider von Deimling, T., Lee, H., Ingeman-Nielsen, T., Westermann, S., Romanovsky, V., Lamoureux, S., Walker, D.A., Chadburn, S., Trochim, E., Cai, L., Nitzbon, J. Jacobi, S., & Langer, M. (2020). Consequences of permafrost degradation for Arctic infrastructure–bridging the model gap between regional and engineering scales. *The Cryosphere Discussions*, *2020*, 1-31.

Schuur, E. A., McGuire, A. D., Schädel, C., Grosse, G., Harden, J. W., Hayes, D. J., ... & Vonk, J. E. (2015). Climate change and the permafrost carbon feedback. *Nature*, *520*(7546), 171-179.

Smith, S. L., O'Neill, H. B., Isaksen, K., Noetzli, J., & Romanovsky, V. E. (2022). The changing thermal state of permafrost. *Nature Reviews Earth & Environment*, *3*(1), 10-23.

Swanson, D. K., Sousanes, P. J., & Hill, K. (2021). Increased mean annual temperatures in 2014–2019 indicate permafrost thaw in Alaskan national parks. *Arctic, Antarctic, and Alpine Research*, *53*(1), 1-19.

Thaler, E. A., Uhleman, S., Rowland, J. C., Schwenk, J., Wang, C., Dafflon, B., & Bennett, K. E. (2023). High-resolution maps of near-surface permafrost for three watersheds on the Seward Peninsula, Alaska derived from machine learning. *Earth and Space Science*, *10*(12), e2023EA003015.

Treat, C. C., Jones, M. C., Alder, J., Sannel, A. B. K., Camill, P., & Frolking, S. (2021). Predicted vulnerability of carbon in permafrost peatlands with future climate change and permafrost thaw in Western Canada. *Journal of Geophysical Research: Biogeosciences*, *126*(5), e2020JG005872.

Wang, Y., Chen, X., Gao, M., & Dong, J. (2022). The use of random forest to identify climate and human interference on vegetation coverage changes in southwest China. *Ecological Indicators*, *144*, 109463.

Westermann, S., Ingeman-Nielsen, T., Scheer, J., Aalstad, K., Aga, J., Chaudhary, N., ... & Langer, M. (2023). The CryoGrid community model (version 1.0)–a multi-physics toolbox for climate-driven simulations in the terrestrial cryosphere. *Geoscientific Model Development*, *16*(9), 2607-2647.

Wheeler, D., Shaw, G., & Barr, S. (2013). Statistical techniques in geographical analysis, (chap. 9, pp. 193–199). Routledge.

Yin, G., Luo, J., Niu, F., Lin, Z., & Liu, M. (2021). Machine learning-based thermokarst landslide susceptibility modeling across the permafrost region on the Qinghai-Tibet Plateau. *Landslides*, *18*(7), 2639-2649.

Zhao, L., Xie, C., Yang, D., & Zhang, T. (2021). Ground Temperature and Active Layer Regimes and Changes. *Arctic Hydrology, Permafrost and Ecosystems*, 441-470.

Zhang, C., Douglas, T. A., & Anderson, J. E. (2021). Modeling and mapping permafrost active layer thickness using field measurements and remote sensing techniques. *International Journal of Applied Earth Observation and Geoinformation*, *102*, 102455.

Zhang, M., Li, R., Pei, W., Zhou, Y., Li, G., & Yang, S. (2024). Permafrost Degradation Risk Evaluation in the Qinghai-Tibet Plateau Under Climate Change Based on Machine Learning Models. *Journal of Geophysical Research: Atmospheres*, *129*(2), e2023JD039611.