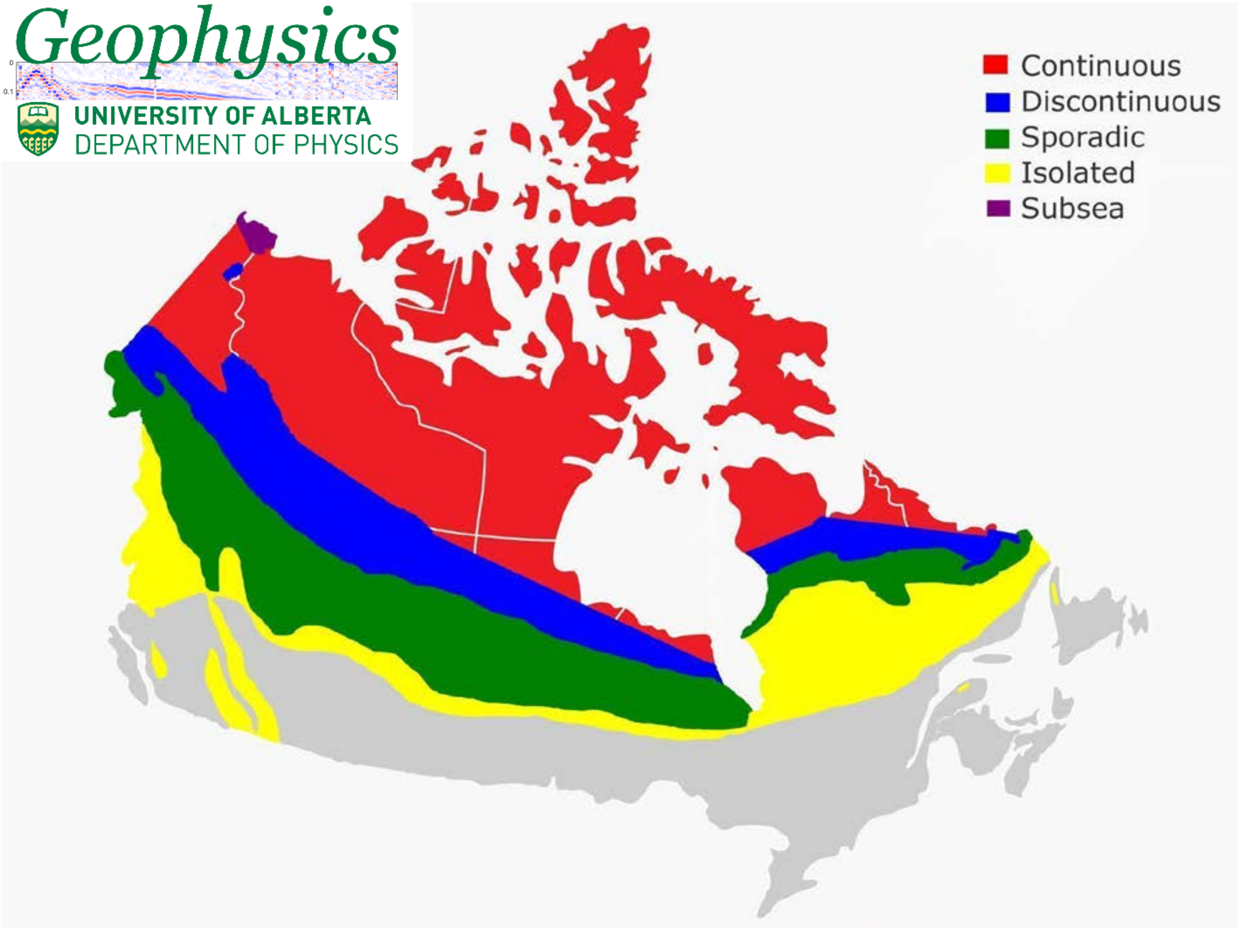

1st year project report (2023-2024)

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 2024

* Correspondence to vadim@ualberta.ca

Abstract

Over the past few years, significant advancements in machine learning (ML) techniques have enabled us to analyze complex environmental data with unprecedented efficiency and precision. ML models excel at uncovering relationships between dependent variables and various explanatory factors. Unlike traditional physics-based models, ML models provide a flexible framework for exploring environmental conditions related to topography and land cover, aspects that are often challenging to capture using only physical parameters. This report presents our first-year results on numerical modelling of permafrost thawing based on various parameter records from the Northwest Territories. We tested the capabilities of ML algorithms in analyzing permafrost thaw dynamics in the study area and implemented the ML techniques Random Forest and Neural Networks using the Matlab programming language for numeric computing. Our regression analysis of the selected data demonstrated the ML techniques' capability to construct temperature change predictions from training with actual observational data. The Neural Networks algorithm exhibited rapid learning and optimization capabilities, effectively capturing the complex relationships governing permafrost thaw rates. Mean Squared Error and error distribution analyses further confirmed the precision and reliability of the preliminary ML models in predicting temperature variations. The application of the Random Forest algorithm for predicting Mean Annual Ground Temperature revealed satisfactory predictive power and suggested directions for improvement and refinement in the next reporting year. Our study lays the groundwork for more detailed future analyses and enhancing predictive model accuracy for permafrost thaw dynamics using ML techniques.

1. Introduction

Climate change poses unparalleled challenges, especially in permafrost regions, which calls for a thorough understanding of permafrost dynamics and how permafrost thawing affects the environment and infrastructure (Jones et al., 2023). With an emphasis on the Northwest Territories, this report for the period of October 2023 to March 2024 implements the use of machine learning and numerical modelling techniques to assess permafrost thawing dynamics and rates. Machine learning (ML) techniques have advanced substantially in the last few years, allowing us to evaluate intricate environmental data with previously unheard-of efficiency and accuracy, allowing for more accurate forecasts and well-informed decision-making across a range of ML environmental prediction applications (Rolnick et al., 2022). ML models are capable of elucidating the relationship between a dependent variable and other explanatory variables (Wheeler et al., 2013).

A key component of our analysis is the numerical modelling of thawing permafrost rates. Ni et al. (2021) were the first to successfully implement the ML to predict future permafrost changes on the Qinghai-Tibet Plateau. In support of this strategy, Li et al. (2023) emphasized the potential of ML models in assessing thaw settlement risks. Due today, the ML has not been tested for permafrost thaw rate predictions in Canada and North America. In this study, we strategically chose and applied the most effective up-to-date ML techniques to the available data. Implementing our ML strategy to automate what was previously a manual, iterative process will significantly increase the accuracy of predictions regarding how permafrost responds to climate change. This advanced approach opens the possibility of integrating our ML techniques into the widely used community model, CryoGrid (Westermann et al., 2023), enhancing its predictive capabilities and efficiency in future permafrost research.

We will also integrate the movement of contaminants in soils affected by frost into our project, providing a critical perspective on the environmental impacts of permafrost thawing (Adams, 1998). This aspect is particularly relevant given the increasing concern about the stability and integrity of infrastructure, such as drilling waste sumps, in permafrost thawing regions. Additionally, Yin et al. (2021) made a substantial contribution to our comprehension of modelling landslide susceptibility in permafrost regions. Their ML-based thermokarst landslide susceptibility modelling on the Qinghai-Tibet Plateau will be incorporated into our methodology for assessing similar risks in the Northwest Territories in the following years of our project.

We used the multi-year data from the NWT Open Report (2019-012) that provides a comprehensive synthesis of the permafrost conditions in the Inuvik-Tuktoyaktuk region (Ensom et al., 2019). The available data were acquired from the geotechnical boreholes along the Inuvik to Tuktoyaktuk Highway corridor (Figure 1).

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).

Our analysis and modelling have been aided by insights from the NWT Open Report, especially in regard to comprehending the variations in substrate characteristics across the study area and the changes in ground temperature. The data includes the Active Layer Thickness (ALT) and

Mean Annual Ground Temperature (MAGT), allowing us to assess its vulnerability and create a baseline for future modifications. MAGT and ALT assessment and adjustments are critical to determining the areas where permafrost is thawing more rapidly. The parameter modelling will allow us to predict how permafrost will react to various greenhouse gas emissions scenarios to pinpoint the melting locations and thawing rates. This report tests the feasibility and performance of the most advanced to-date ML techniques to provide a thorough picture of the present and potential effects of permafrost thawing in the study area. Currently, high-accuracy physics-based mechanistic models are the favoured approach for permafrost thawing predictions (Westermann et al., 2022). However, such an approach is often limited by data scarcity and a trade-off between modelling resolution and geographical scope. Conversely, ML techniques have emerged as a promising approach to address these limitations. ML techniques are effective in capturing complex, non-linear relationships in the data that conventional methods might overlook. For example, an ML-based model is capable of extracting information about certain combinations of soil moisture levels, summer temperatures, and vegetation types, which are strong predictors of rapid thawing in specific regions (Ni et al., 2020; Li et al., 2023).

2. Methodology

2.1. Machine Learning (ML)

Different approaches to data analysis and predictive modelling are provided by different ML methods. Neural Networks and Random Forest are up-to-date and highly effective techniques, each with unique benefits and applications. An outline of these two approaches is given in this section, along with information on their theoretical underpinnings and real-world applications within the framework of our investigation. We performed the following data treatment ML procedures:

- Training: The ML model learns to predict outcomes from the available field data. In permafrost research, the model would learn how changes in the variable assemblage, such as temperature, soil properties, water content, and snow depth, relate to permafrost thawing.
- Validation: This step adjusts the model to ensure it generalizes well to new data, avoiding overfitting.
- Testing: The model is evaluated on unseen data to confirm its predictive ability.

The results of these procedures implemented on a selected data set will be discussed in Section 3. All available data will be analyzed in the next reporting year.

2.1.1. Random Forest

The Random Forest (RF) algorithm excels in handling complex datasets with numerous variables, such as temperature, precipitation amount, snow depth, wind strength, soil properties, etc. Its proficiency in managing high-dimensional data and mitigating overfitting makes it an effective choice for simulating the nonlinear dynamics of permafrost. This approach enhances accuracy and facilitates the identification of critical factors influencing permafrost thawing that may differ between study site locations.

Overfitting poses a significant challenge in ML, especially for intricate models like those used for forecasting permafrost fluctuations. Overfitting occurs when a model poorly generalizes to new data because it has memorized noise and specific fluctuations in the training set. RF addresses this issue by employing multiple trees to improve prediction generalization. Additionally, its design obviates the need for data scaling, simplifying data preparation and providing a distinct advantage in permafrost studies with varying data scales. This ensures the effectiveness and efficiency of the model in detecting significant changes (Kulkarni & Sinha, 2013). In our methodology, the RF algorithm will be employed to analyze the field data and provide insights into overall predictive accuracy and various parameter relevance. The RF algorithm employs a bootstrap sampling technique to derive multiple samples from the original dataset. For each sample, decision tree modelling is performed, and the predictions of multiple decision trees are aggregated through a voting process to produce the final prediction outcome.

Two of the most important factors needed for our calculations are MAGT and ALT. The thawing indices (thawing degree days, TDD) and the freezing indices (freezing degree days, FDD), site longitudes (Lon) and latitudes (Lat) will play essential roles in our modelling. Potential incoming solar radiation (PISR), soil organic carbon (SOC), elevation (Ele), solid precipitation (Sol_{pre}), liquid precipitation (Liq_{pre}) are other variables. To study the effects of these factors on MAGT and ALT, our models will be designed using the following specifications (Ni et al., 2021):

$$\text{MAGT}=f_1(TDD)+f_2(FDD)+f_3(Sol_{pre})+f_4(Liq_{pre})+f_5(PISR)+f_6(SOC)+f_7(Lon)+f_8(Lat)+f_9(Ele) \tag{1}$$

$$\text{ALT}=f_1(TDD)+f_2(FDD)+f_3(Sol_{pre})+f_4(Liq_{pre})+f_5(PISR)+f_6(SOC)+f_7(Lon)+f_8(Lat)+f_9(Ele) \tag{2}$$

The independent variables remain consistent across these equations, yet the corresponding function $f_i(x_i)$ differs for each. f_i is a smoothing function for each explanatory variable, and x_i is a predictor. An ensemble approach will be employed to comprehensively evaluate the strengths and weaknesses of the RF future models and reduce uncertainty. This approach will aggregate the averages of the RF models to generate new results. The RF model performance will be evaluated using a repeated cross-validation scheme (section 3.5).

2.1.2. Neural Networks

A subclass of ML algorithms known as Neural Networks (NNs) stands out for their ability to tackle complex nonlinear prediction and pattern recognition tasks, making them well-suited for investigating changes in permafrost. Their adaptability enables modelling nonlinear data relationships across various applications, including image recognition and time series analysis. NNs offer a flexible structure that can be tailored to specific data features through various configurations such as feedforward, convolutional, and recurrent networks.

By learning from data, NNs refine their predictive accuracy by adjusting weights to minimize prediction errors. In the realm of permafrost research in the Northwest Territories, neural networks will be utilized to discern intricate data patterns. These patterns describe the complex and nonlinear interactions within data and encapsulate the dynamics of environmental systems. These interactions are frequently observed in permafrost variables, such as temperature fluctuations, geographical diversity, and annual or multiyear climatic variations.

Training dynamics over epochs is the final step in NNs. The local minima serve as starting points for further optimization techniques, allowing for the refinement of the model’s performance. Typically, training would be terminated early to avoid overfitting if the validation performance did not improve after a certain number of epochs. The Mean Squared Error (MSE) measures the average squared difference between the predicted and actual values, serving as a quantifiable metric of the model’s prediction error. The MSE is a critical indicator of the model's accuracy across the training, validation, and test phases. Gradient norm, learning rate, and validation checks are three metrics that illustrate the NNs model's efficiency toward high accuracy and robust generalization abilities.

We face rapid learning in the context of the NNs training, which refers to a period at the beginning of the training process where the model quickly improves its ability to predict or classify data correctly. This is often seen as a steep decrease in error rates, such as the MSE, during the initial epochs (an epoch is one complete pass through the entire training dataset). This phenomenon occurs because, at the start of training, the weights of the NNs are usually initialized to small random values, and the model is far from optimal performance. As training begins and the model starts learning from the data, it makes significant adjustments to its weights, leading to large improvements in prediction accuracy. This training phase is characterized by the model "rapidly learning" the basic patterns or structures within the dataset. After this initial phase, as the model starts to converge towards an optimal set of weights, improvements in accuracy or decreases in error rates become more gradual. This is because the model has already learned the major patterns in the data and further fine-tunes the model's performance, requiring more subtle data weight adjustments (Baghirli, 2015).

In the context of permafrost research, NNs modelling involves understanding feedback mechanisms like greenhouse gas emissions from thawing ground and how permafrost responds to climate change and its spatial distribution disparities. NNs excel in learning from data and modelling nonlinear relationships, thereby aiding in deciphering these intricate patterns that will offer us deeper insights and accurate predictions regarding permafrost dynamics. A local minimum found during the NNs analysis by using the evolution of gradient norms represents a point with a minimized difference between predicted and actual values.

2.2. Machine Learning in Permafrost Analysis

The three main goals of our project are all enhanced by the benefits that ML techniques provide. The first goal is to assess how permafrost thawing will affect areas with mud-drilling sumps and associated infrastructure using ML techniques. The ML approach may accelerate the standard process of manual search of relationships between permafrost parameters. For example, temperature increases and permafrost thawing rates pinpoint temperature thresholds above which permafrost starts to thaw more quickly in the Northwest Territories. These thresholds can be derived by examining historical temperature data and permafrost conditions. The stability of permafrost is also affected by changes in vegetation and ALT above permafrost. ML models predict how variations in vegetation types impact the moisture content and ground insulation of permafrost, as well as how increased precipitation can either thaw or insulate it, depending on temperature, precipitation and other factors. This enhanced efficiency enables swift and comprehensive simulation of the future state of permafrost and facilitates the analysis of data from diverse sources.

Our second goal is to calibrate the site-level model and conduct a sensitivity analysis. This step of detecting differences between our model predictions and observational data is essential to simulate future permafrost conditions accurately based on the input data. The process will refine the models' parameters by comparing model predictions with actual observational data and identifying discrepancies. The calibration and sensitivity analysis ensure that the models can reliably predict the permafrost thawing rates. Our third goal is to predict how fast permafrost melts in different parts of the Mackenzie River Delta. The ML algorithms will help us identify key factors that affect permafrost thawing and its consequences, ensuring our predictions are accurate and relevant to current environmental challenges.

We adapted the available Matlab toolboxes for ML. Statistics and ML Toolbox provides functions and apps to describe, analyze, and model data, including RF. We apply the RF algorithm for classification and regression tasks. The NNs toolbox offers a variety of neural network architectures, such as feedforward, convolutional, and recurrent neural networks. These networks can be trained using various optimization algorithms and applied to regression tasks. While Matlab provides these toolboxes, the effectiveness of our modelling depends on the quality and quantity of available data, the complexity of the data relationship and permafrost dynamics, and our implementation programming codes.

2.3. Data Description

This study uses detailed ground temperature data collected from 16 Sentinel sites along the Inuvik to Tuktoyaktuk Highway during 2017 and 2018 (Ensom et al., 2019; Rudy et al., 2019). It records temperatures at various depths monthly to monitor the warmth patterns of the road embankments and the frozen ground underneath. Additionally, we use the data on soil properties in the same area, including its active layer thickness, texture, and composition. The datasets include (***a***) sedimentological data in the borehole (depth, liquid content in the soil, soil composition, texture of the soil, vegetation cover, snow) and (***b***) site condition data (longitude and latitude, elevation, depth of layers in permafrost, temperature, date and time).

Our data processing procedures include (i) ensuring that any missing or inconsistent data is appropriately managed to maintain the dataset's integrity and completeness, (ii) data standardizing and converting non-numeric data into a numeric format, and (iii) extracting relevant features from the raw data that could influence permafrost thawing rates, such as temperature trends, precipitation levels, soil composition, land cover types, elevation, and human activities. In our analysis, we prioritized temperature and depth as key factors because of their important role in understanding permafrost dynamics. There are different datasets, so their analysis is done in several phases. In the first phase, we developed a dataset specifically focused on these parameters. A specific pit 312_Pit_NTGS13 was selected for the initial investigation. This pit’s observational data included longitude, latitude, time, date and temperature in depths of 1, 2, 4, 7 and 10 meters. Similar analyses were performed on pits that had similar observational parameters.

In the next year of the project, we will add precipitation, air temperature, TDD, FDD, PISR, and SOC to our analysis. All data must be checked and then integrated into several ways, and therefore, due to their different nature, checking and applying the algorithm on them and finally analyzing them will be carefully performed. When modelling the relationship between temperature and other non-temperature parameters, the expectation is to uncover how the air temperature influences or correlates with these variables in the context of permafrost studies. This could reveal complex, nonlinear interactions, showing how factors such as soil moisture, vegetation cover, and geographic features interact with temperature to affect permafrost dynamics. The model aims to provide insights into the sensitivity of permafrost to climate change, identify key drivers of permafrost thaw, and enhance predictions of permafrost behaviour under different climate scenarios.

We use the RF technique to analyze how permafrost thaw rates might increase or decrease due to temperature variations in the summer and winter and determine which environmental factors have the most significant impact on thaw rates. We further utilize the NN algorithm to explore the interaction between variables in 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.

3. Results for 2023–2024

Our main effort in the first year of the report was to adapt, test, and implement the ML approaches and develop the Matlab codes. We started with the selected pit 312_Pit_NTGS13. Depth at 1 meter is closest to the surface, and the top of the ALT is considered as a starting point. So, temperature and depth measurements at 2 and 4 meters were the most important parameters influencing the dataset by the analysis, with corresponding importance scores of 0.0509 and 0.0290 calculated using the RF approach. These depths correspond with ALT, the topmost layer of soil that thaws in the summer and refreezes in the fall. With an importance score of 0.0221, the time of the year has a direct influence on the dynamic nature of permafrost. Furthermore, although less significant, deeper depths (10 and 7 m) and observation dates demonstrated scores of 0.0072, 0.0098 and 9.4524×10^{-5}, respectively. Parameters with higher scores are considered primary influencers of permafrost thaw. These are the variables that our further analysis will prioritize. Understanding the relationship between these high-impact factors and permafrost thaw will lead to more accurate predictions. While parameters with lower scores might have a smaller direct impact on thaw rates, they are not necessarily irrelevant. They could play significant roles under specific conditions or in combination with other factors. However, in the interest of efficiency and focus, our analysis might deprioritize these in favour of more influential variables.

3.1. Evaluation of Model Predictive Performance through Regression Analysis

The Regression Analysis (RA) helps us find and focus on the areas most likely to be affected by permafrost thaw. We started with RA using regression analysis because it is essential for making our neural network model good at predicting future changes. The results include charts that show how well the model did with different groups of data during the learning, checking, and testing phases. These charts help us see how close the model's guesses are to what actually happens. We obtained an R-value of 0.99997, which is nearly the highest possible. It signifies that our predictions match observations Y=T, and our ML model's guesses are very close to the actual data values (Figure 2).

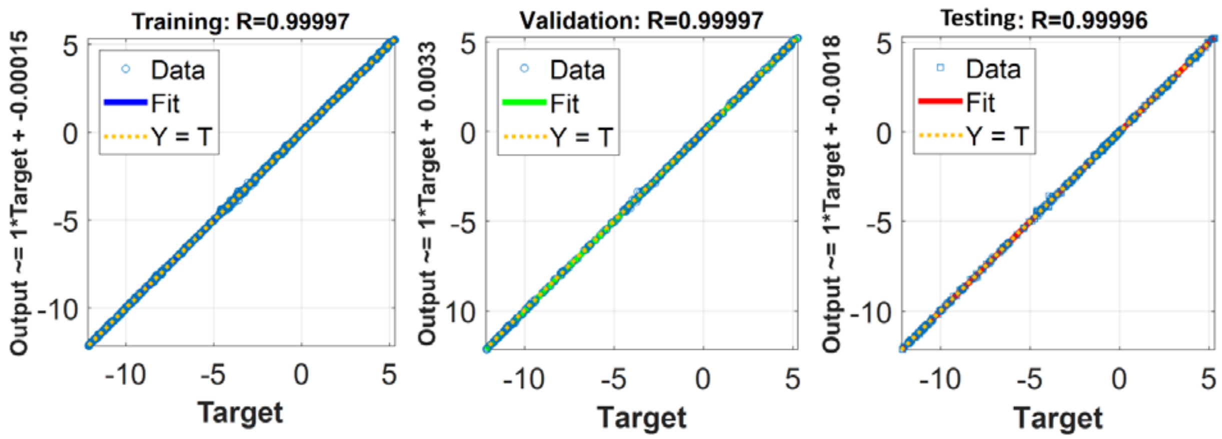

Figure 2. Comprehensive regression analysis demonstrating the high correlation between temperature in ALT and temperature values for different depths across machine learning training predicted outputs, validation, and test datasets.

3.2. Analysis of Neural Network Training Progression

The Neural Networks model's evolution of key training parameters over a thousand epochs[1] is depicted in Figure 3, which offers insights into the optimization process and the model's learning efficiency. The choice of 1,000 epochs is not fixed; it is a starting point to ensure the model has enough opportunities to learn patterns within the data, particularly those affecting permafrost thaw rates, such as temperature variations and ALT. The gradient descent plot reflects the model's learning process as it attempts to minimize prediction errors related to the temperature profiles at various depths and their impact on the active layer thickness (Figure 3a). A steep decline in the gradient norm reaching a minimum value of 0.0013533 suggests that the model quickly identified significant patterns and relationships in the early stages of training. As the gradient levels off, it indicates that the model has reached a stable understanding of how temperature variations at one meter relate to those at other depths and ALT. This plateau suggests that further adjustments to the model parameters yield only marginal improvements, signifying an optimization of the model's predictions regarding the environmental factors of the study (Figure 3a).

The adaptive adjustments to the learning rate (mu) throughout the training process demonstrate the model's refinement in understanding the complex relationships between the different variables, including the time of the year and its effects on the permafrost. The step-wise reduction in mu suggests a strategic approach to learning, where initial larger steps help the model rapidly converge towards a good fit for the data in the test pit, it highlights variables like

[1] An "epoch" in ML refers to one complete cycle through the entire training dataset, during which the ML model updates its internal parameters to improve performance.

temperature, ALT and time of the year that are more important and does not ignore variables that are less important like deeper depth, longitude and latitude. It is followed by smaller steps to fine-tune the predictions about temperature relationships and active layer thickness. This adaptive strategy ensures that the model does not overlook subtle yet critical patterns in the data, enhancing its predictive accuracy and reliability (Figure 3b).

The validation checks, which count the number of epochs since the last improvement on the validation set, are displayed in the third subplot (Figure 3c). During the training process, this count stays at zero, which is a strong indicator of the model's successful learning and generalization until the end of the training period. It shows that the model's performance on the validation set continuously improved or stayed optimal. Later, it can help us to find the relationship between MAGT and ALT because the training process for non-linear relationships is completed.

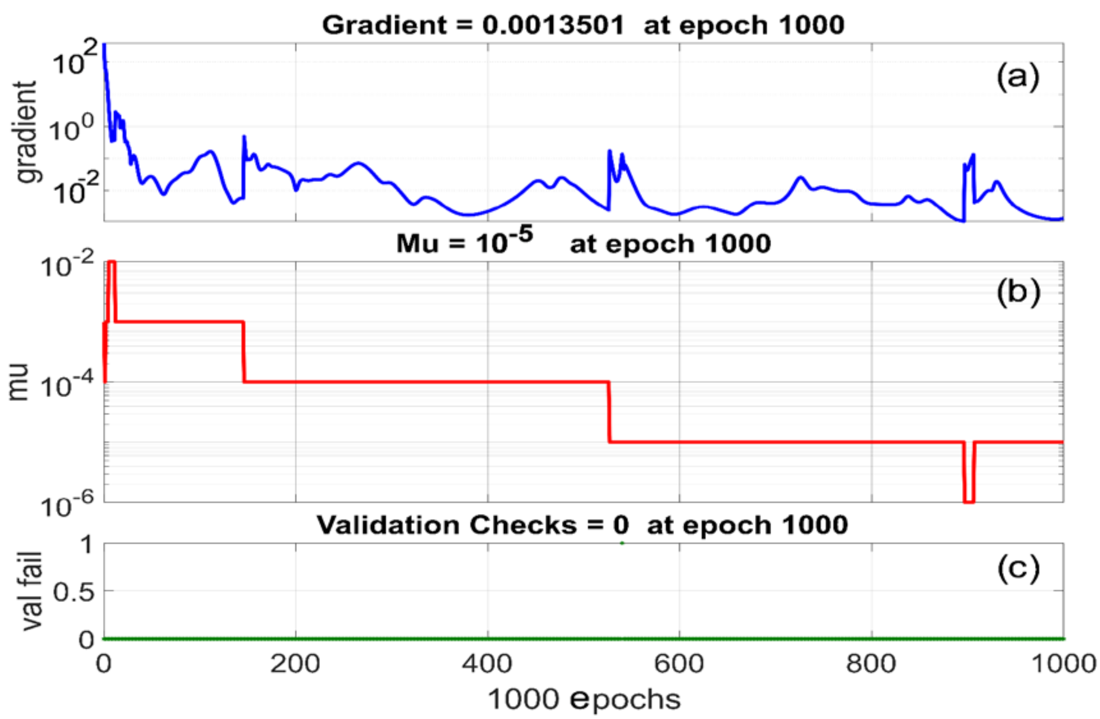

Figure 3. Training dynamics of the Neural Network over 1000 epochs. (a) The gradient is the loss function, which measures how far off the model's predictions are from the actual values. (b) The learning rate (mu) throughout the training process demonstrates the model's refinement in understanding the complex relationships between the different variables. (c) Validation fail (val fail) is a validation failure that is counted when the model's performance on the validation set does not improve; this graph indicates that the model's performance on the validation data was stable or improving throughout the training process.

3.3. Assessment of Model Accuracy through the Mean Squared Error Analysis

Figure 4 shows a quick drop in the MSE for the training, validation, and testing phases at the start, indicating fast learning by the ML model. As the training progresses, the decrease in MSE decreases, suggesting the model is nearing its best performance, demonstrating the NNs' strong performance and ability to generalize prediction data effectively. Therefore, this performance can be shown in other pits. With an MSE value as low as 0.0017086, the "Best" performance at epoch 1000 shows that the model either maintained or improved its performance throughout training.

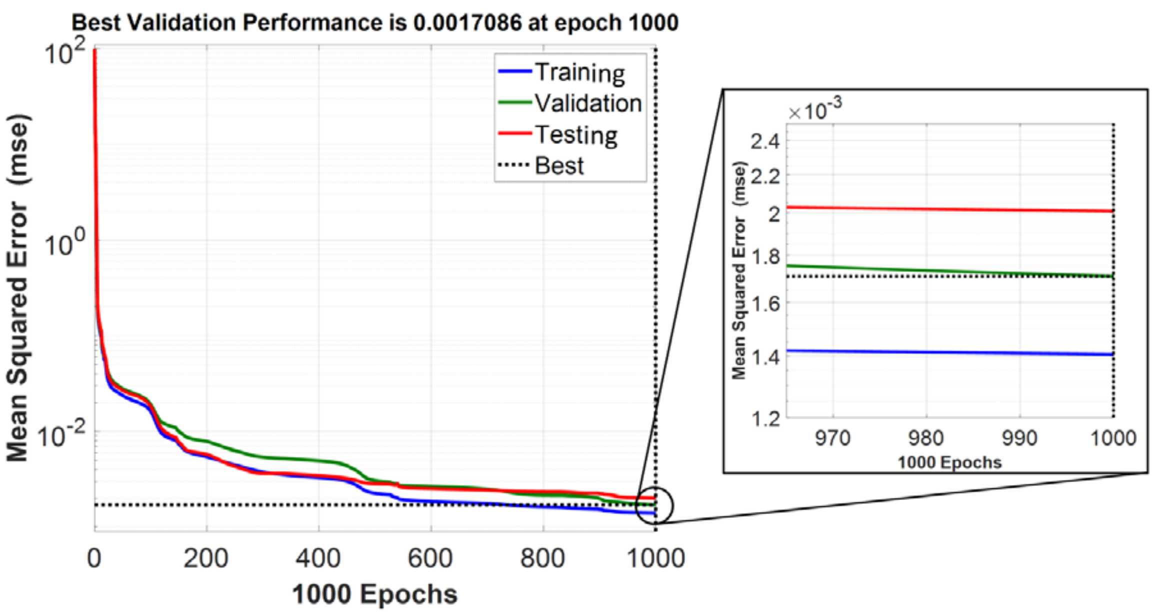

Figure 4. Mean Squared Error trajectory across training, validation, and testing. The insert in the top right corner is a magnified view of the MSE from epochs 970 to 1000 for a more detailed look at the convergence of the error rates. This zoomed view shows that the errors have plateaued, indicating that additional training beyond 1000 epochs may not yield significant improvements. The term "Best" in the figure caption refers to the best validation performance obtained during the training process. This is the lowest value of the validation error, which occurred at epoch 1000, with an MSE of 0.0017086. This point is likely used to stop the training (a technique known as early stopping) to prevent overfitting, where the model learns the training data too well, including its noise and outliers, which could degrade its performance on unseen data.

3.4. Analysis of Error Distribution via Histogram

The error histogram graph (Figure 5) from the study on permafrost effectively showcases a narrow, bell-shaped distribution centred around zero, underscoring the model's high accuracy in predicting how temperature varies with depth. This central concentration of errors near zero, coupled with the distribution's narrow spread, highlights the model's precision and its unbiased nature in estimating temperatures. The symmetry of the distribution further confirms the model's consistent performance across various conditions, with only a handful of outliers indicating rare deviations. Overall, this graph serves as a visual testament to the successful application of the NNs model in capturing the linear relationship between temperature and depth in permafrost studies based on monthly collected data, validating the methodology and precision of the predictions made.

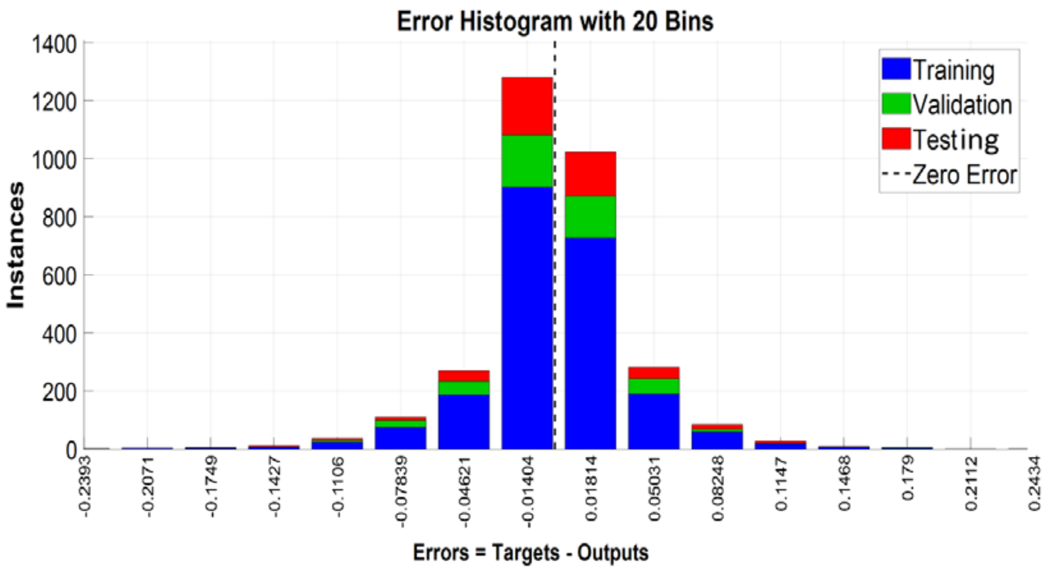

Figure 5. Distribution of prediction errors in the NNs model.

3.5. Reliability Assessment of MAGT

We used the RF algorithm to test the feasibility of predicting MAGT, which is identified as a significant factor influencing permafrost behaviour. Our intermediate result for 16 study sites is shown in Figure 6. To make the initial prediction, we used data such as depth, site longitude and latitude, the temperature at different depths, soil properties, and liquid in the soil. After each cross-validation run, the predicted and observed values of MAGT and ALT were compared in terms of the root-mean-square error (RMSE), mean difference (Bias), and R-squared (R^2). The RMSE value of 0.73 demonstrates that the predicted MAGT values are, on average, close to the actual measurements. In the context of MAGT predictions, an RMSE value of less than 1 is generally considered to be very good. The minimal bias observed indicates that the model tends to slightly overestimate MAGT values. However, this bias is relatively minor, suggesting that the model does not exhibit a strong systematic error in any specific direction.

The black line represents the 1:1 line, illustrating an ideal scenario where predicted MAGT values would precisely match the actual MAGT values. In a perfect scenario, all the blue dots, which represent the predictions, would align with this line. The red dashed lines depict the boundaries of the RMSE, indicating where the majority of predictions fall in relation to the actual values. The accuracy of the predictions increases as more dots are closer to the black line and fewer dots are found between the red dashed lines.

An R^2 value of 0.55 indicates that our RF model accounts for 55% of the variance observed in the actual MAGT data. This suggests that at this stage of the project, the RF algorithm possesses moderate predictive power but also highlights that nearly half of the variance in MAGT is not explained by the model. This outcome is considered intermediate, indicating room for improvement in the RF model's accuracy. For future enhancements, we will incorporate additional important parameters such as elevation, soil organic carbon (SOC), potential incoming solar radiation (PISR), freezing degree days (FDD), thawing degree days (TDD), air temperature, and precipitation. By integrating all these data, we anticipate achieving a more accurate simulation of MAGT in the next reporting year.

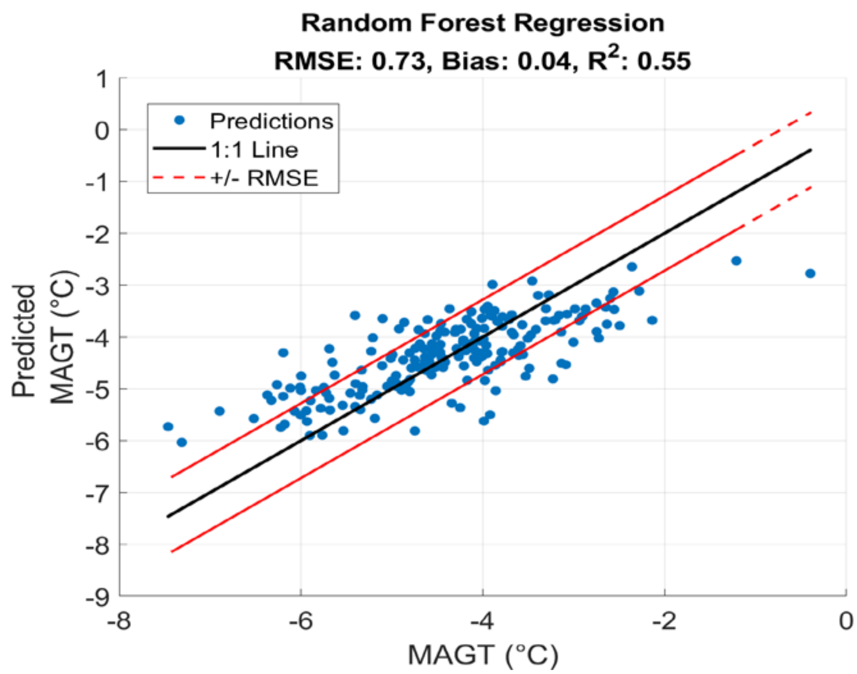

Figure 6. Observed versus simulated mean annual ground temperature (MAGT, represented by the blue dots) for 16 sites, including samples from the boreholes, pits, and measurement points at the sites. Following each cross-validation iteration, the predicted and observed MAGT values were compared using metrics such as root-mean-square error (RMSE), mean difference (Bias), and R-squared (R^2). The black line 1:1 depicts an ideal scenario where predicted MAGT values should align with the actual MAGT values.

4. Conclusions

This report demonstrates our progress in understanding permafrost thaw dynamics through the integration of ML techniques and numerical modelling. In the first year report (6 months) we concentrated our work on adapting ML approaches and developing Matlab codes focused on selected testing data, the RF method helped to understand the importance of parameters and to identify temperature at specific depths as primary influencers of permafrost behaviour. The Regression Analysis in the Neural Networks Training Progression demonstrated the model’s high predictive performance and accuracy with low MSE. There is a strong relationship between variables, showing predictable changes. It signifies that the model's predictions are very close to actual values. By applying the RF and NNs approaches to the testing data from pit 312_Pit_NTGS13, we conclude that the algorithm is effective in recognizing the important relationship between temperature and ALT. The simulation of MAGT by using RF displayed a high accuracy, however, it can be improved by involving more parameters in the calculation in future work. By applying the algorithms to the rest of the available data, we plan to model the relationship between all parameters in different sites with different environmental and geological conditions. We plan to use the ML methods to further explore complex relationships within permafrost systems and refine predictive capabilities to better inform mitigation strategies against permafrost thaw impacts.

5. Future work 2024-2025

In the continuation of the project, our primary focus will be on completing the comprehensive analysis of all datasets. This entails conducting a thorough examination of each type of data source to gain a deeper understanding of the intricate dynamics of permafrost thaw. We will further scrutinize ground observations, including borehole temperature, soil moisture levels, and active layer thickness, similar to our approach with the 312_Pit_NTGS13 pit data discussed in the report. This will involve executing necessary preprocessing steps such as data cleaning, addressing missing values, formatting adjustments, and assessing correlations between variables. These ground measurement data will provide tangible evidence of permafrost condition changes and serve as crucial validation for other data sources. In addition, we will use the satellite imagery data to monitor temporal changes in land surface temperatures, vegetation cover, and ice/water bodies. This procedure will aid us in pinpointing regions undergoing permafrost degradation or where surface alterations indicate thawing processes in action.

In the next reporting period, our focus will shift toward attribute analysis for Active Layer Thickness (ALT) and improve Mean Annual Ground Temperature (MAGT). This will involve a rigorous statistical exploration of the relationships between these permafrost features and other environmental variables (e.g., surface temperature, snow cover, vegetation, and soil properties). Leveraging methodologies such as Random Forest and Neural Networks, we will discern the most influential variable thresholds that impact MAGT and ALT. At the moment, in the numerical modelling of the permafrost thawing, the thresholds are usually manually selected using the time-consuming iterative procedure. Our ML process to replace the manual iterative procedure will enhance the precision of permafrost response to climate change predictions. In the future, this process could be incorporated into the community code CryoGrid (Nitzbon et al., 2020).

Finally, we will embark on the numerical model of permafrost thawing development. This phase entails crafting predictive models that leverage insights gleaned from initial data analyses to forecast future permafrost conditions. Integrating machine learning techniques with statistical analyses, these models will be designed to be robust, capable of handling diverse data variability, and adaptable to incorporate new data or insights as they emerge. Our overarching objective is to develop numerical models that accurately simulate permafrost responses across varying climate scenarios, accounting for regional factors and specifics and the complex interplay of factors such as temperature fluctuations, snow cover dynamics, and shifts in vegetation patterns.

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

Adams, B. (1998). Contaminant movement in frost-affected soils (Doctoral dissertation, Carleton University).

Baghirli, O. (2015). Comparison of Lavenberg-Marquardt, scaled conjugate gradient and Bayesian regularization backpropagation algorithms for multistep ahead wind speed forecasting using multilayer perceptron feedforward neural network.

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.

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.

Kulkarni, V. Y., & Sinha, P. K. (2013). Random forest classifiers: a survey and future research directions. Int. J. Adv. Comput, 36(1), 1144-1153

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.

Ni, J., Wu, T., Zhu, X., Hu, G., Zou, D., Wu, X., Li, R., Xie, C., Qiao, Y., Pang, Q., Hao, J., & Yang, C. (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.

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.

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

Westermann, S., Ingeman-Nielsen, T., Scheer, J., Aalstad, K., Aga, J., Chaudhary, N., Etzelmüller, B., Filhol, S., Kääb, A., Renette, C., Schmidt, L. S., Schuler, T. V., Zweigel, R. B., Martin, L., Morard, S., Ben-Asher, M., Angelopoulos, M., Boike, J., Groenke, B., Miesner, F., Nitzbon, J., Overduin, P., Stuenzi, S. M., & 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.

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, 2639-2649.