https://doi.org/10.5194/egusphere-2025-4478
Preprint. Discussion started: 17 October 2025

Determining TTOP model parameter importance and overall performance across northern Canada

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Key Words: TTOP model, random forest, permafrost, Sensitivity, High Arctic, Subarctic

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https://doi.org/10.5194/egusphere-2025-4478
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Abstract

Modelling current permafrost distribution and response to a warming climate depends on understanding which factors most strongly control ground temperatures. The Temperature at the Top of Permafrost (TTOP) model provides a simple, widely used framework for estimating permafrost presence and thermal state, yet its sensitivity to key parameters remains poorly quantified across diverse northern environments. This study evaluates the relative influence of TTOP model parameters using ground and air temperature data from 330 sites across northern Canada. A leave - one - out cross-validation approach combined with random forest analysis was used to assess both model sensitivity and variable importance. Results show that TTOP performance is dominated by freezing-season conditions—particularly the freezing n-factor and freezing degree days—while thaw-season parameters exert less control. Sensitivity patterns vary by region, with thawing parameters becoming more influential where the duration of the freezing and thawing seasons is similar. Machine-learning results highlight the additional importance of thermal offset and mean surface temperatures, emphasizing the importance of substrate properties. While the model generally reproduces observed ground temperatures well, parameters derived from landcover classes were not transferable between sites, underscoring the importance of locally calibrated inputs. Overall, this study clarifies how different climatic and environmental factors shape the accuracy of permafrost temperature modelling and provides practical guidance for improving parameterization in regional and global permafrost models.

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1 Introduction

Permafrost is an important element of the cryosphere, impacting, for example, terrain stability (Romanovsky et al., 2017; Smith et al., 2022; O'Neill et al., 2023), carbon storage (Miner et al., 2022), and solute movement (Roberts et al., 2017; Lafrenière & Lamoureux, 2019). Unlike other elements of the cryosphere (e.g., glaciers and sea ice), direct observation of permafrost remains challenging (Kääb, 2008) and modelling is often the best way to predict permafrost temperature and distribution.

The Temperature at Top of Permafrost (TTOP) model (Table 2) (Riseborough & Smith, 1998) has been used to estimate permafrost temperature and presence at continental to local scales (Henry & Smith, 2001; Gisnås et al., 2013; Way & Lewkowicz, 2016; Obu et al., 2019; Vegter et al., 2024) and in a variety of permafrost environments including in the High Arctic and in mountains (Bevington & Lewkowicz, 2015; Garibaldi et al., 2021; Garibaldi et al., 2024). Its extensive use for spatial modelling is principally due to its simplicity compared to many numerical models, as well as using input data that are generally measured by meteorological stations. It is also directly transferable to a variety of permafrost environments without the need for recalibration as with empirical-statistical models (Juliussen & Humlum, 2007; Riseborough et al., 2008). A of the primary challenge of using the TTOP model, however, is determining the values of the scaling factors (n-factors) and soil thermal conductivities used for model parameterization (Juliussen & Humlum, 2007). In modelling studies, these scaling factors are typically assigned based on landcover class or topographic class using field measurements or values presented in the literature (Riseborough et al., 2008; Gisnås et al., 2013; Obu et al., 2019). Few studies, however, have examined the uncertainties arising from mischaracterization of the

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value of the TTOP model parameters on the TTOP model output or the relative importance of each parameter in different permafrost environments (Way & Lewkowicz, 2018).

Way and Lewkowicz (2016) demonstrated that utilizing freezing n-factors (n_f) from western Canada when running the TTOP model for Labrador-Ungava reduced the accuracy of model outputs in forested environments. Theoretical and field data have both been used to assess TTOP model variable importance (Smith & Riseborough, 2002; Bevington & Lewkowicz, 2015). These studies highlighted the importance of n_f, especially in High Arctic environments, but also noted the increasing influence of differential thermal conductivity (rk – the ratio between thawed and frozen thermal conductivity) near the southern limit of permafrost. However, these studies relied either on theoretical inputs or measurements covering relatively small study areas, potentially limiting the applicability of the conclusions to other locations or broader scales. As the parameterization of the scaling factors and rk remain one of the main challenges in utilizing the TTOP model, understanding the relative importance and sensitivity of the model to these parameters using empirical data is essential. Quantifying the impacts of input parameter selection will aid model parameterization for future permafrost modelling studies.

Random forest is a supervised machine learning technique, which combines randomized decision trees with bagging, and aggregates their predictions though averaging or majority vote (Breiman 2001; Biau & Scornet, 2016). Random forest has been used in studies of air quality (Yu et al., 2016; Pendergrass et al., 2022), chemoinfomatics (Mitchell, 2014), ecology (Cutler et al., 2007; Brieuc et al., 2018) and remote sensing (Belgiu & Drăgu, 2016). Recently, random forest has been used in spatial mapping of permafrost presence using environmental predictors (topography, rock glaciers, vegetation, and land surface characteristics) in a variety of environments (Pastick et al., 2015; Deluigi et al., 2017; Baral & Haq, 2020). Random forest also

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provides variable importance rankings which can be used to either identify important variables for explanatory or interpolation purposes or to identify a small number of variables that provide a good prediction (Díaz-Uriarte & Alvarez de Andrés, 2006; Grömping, 2009; Genuer et al., 2010). In permafrost environments, these importance rankings have been analyzed for snow depth and landslide potential but have yet to be thoroughly investigated for thermal parameters (Behnia & Blais-Stevens, 2018; Meloche et al., 2022). As the expanded use of machine learning parameterization in conjunction with process-based models may be an important next step for permafrost modelling studies, it is important to understand the variation in variable importance for permafrost temperature across a variety of environments.

The objectives of this study are: (1) to analyze the sensitivity of the TTOP model to incremental changes in parameter value; (2) to test the utility of machine learning for evaluating TTOP model variable importance; and (3) to assess the accuracy of the TTOP model using measured parameters across permafrost regions of Canada. The results should guide efforts to improve TTOP model parameter calculations and to assess the performance of the TTOP model across differing environments.

2 Methods

2.1 Study Area

In situ data used to assess the TTOP model were collected from a variety of Canadian permafrost environments ranging from subarctic to polar desert, in lowlands and mountains (Fig. 1).

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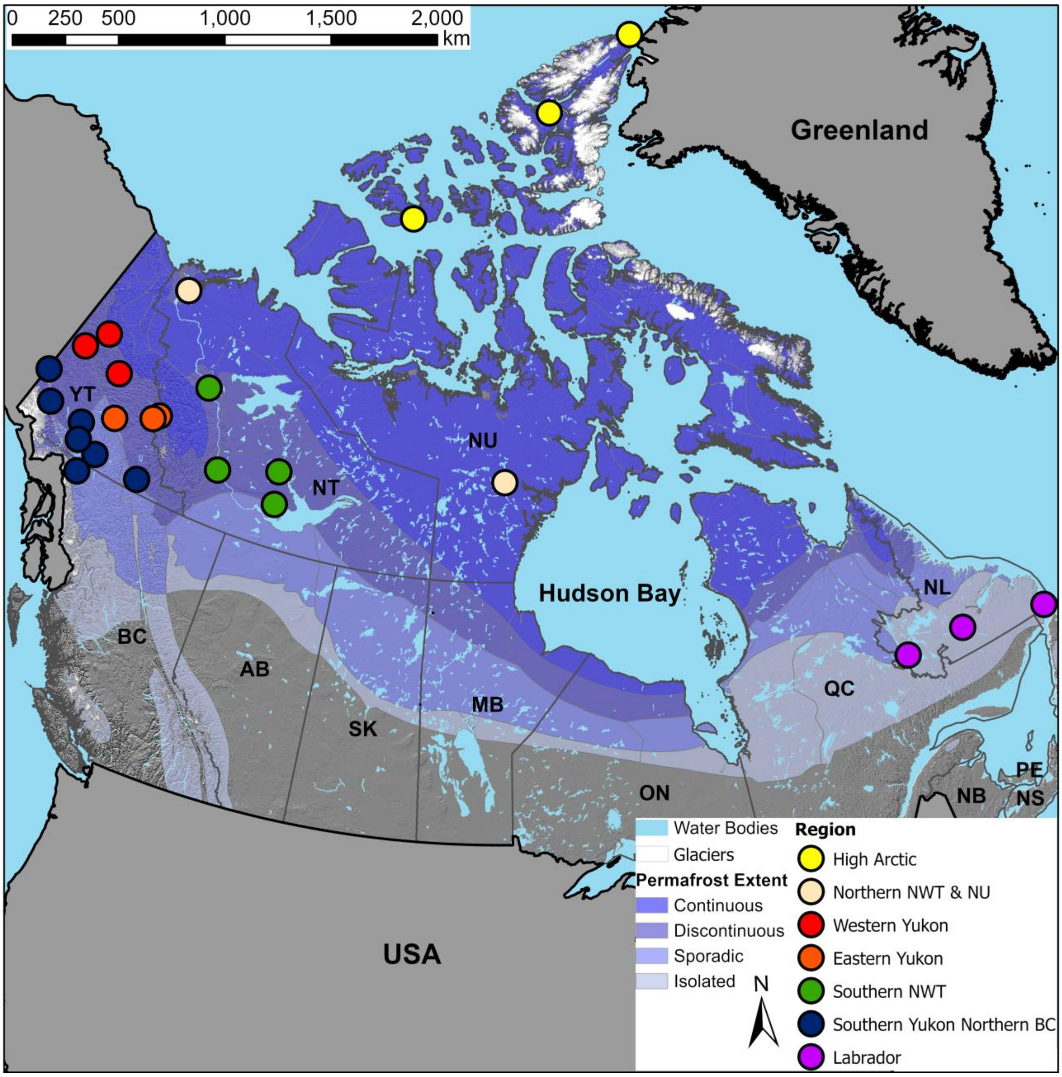

Figure 1. Study area map showing the general location of the study sites used in the TTOP sensitivity analysis and random forest. The sites were grouped into seven regions for analysis (indicated by colour): High Arctic (Queen Elizabeth Islands), Northern NWT & NU, Western Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern British Columbia, and Labrador. Permafrost extent from Brown et al. (2002). Contains information licenced under the Open Government Licence – Canada.

The sampling locations were initially grouped into 21 study areas based on the data source and proximity (Table 1). The latter were then combined into seven main study regions based on similarity in environmental and permafrost conditions and on statistically significant

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differences in model parameters (Table S1): High Arctic, Northern NWT & NU, Southern NWT, Western Yukon, Eastern Yukon, Southern Yukon-Northern BC, and Labrador.

Table 1. Environmental and sampling details for each study area including permafrost condition, mean annual air temperature (MAAT) for the 1991-2020 climate normal from closest EC station (if available), vegetation characteristics, number of sampling locations and length of monitoring period. Total number of observations is the number of individual years of data for each site in the region.(Stanek et al., 1980; Heginbottom et al., 1995; Aylsworth & Kettles, 2000; Smith et al., 2009b; Gregory, 2011; Medeiros et al., 2012; Bevington & Lewkowicz, 2015; Duchesne et al., 2015; Holloway, 2020; Daly et al., 2022; Environment and Climate Change Canada, 2021; Lewkowicz, 2021; Ackerman, 2022; Garibaldi et al., 2024a; Garibaldi et al., 2024b;; Vegter et al., 2024).

Study Area	Grouped Region	MAAT (°C)	Vegetation	Permafrost Condition	Sites with air, ground surface, and ground temperature	Sites with only air and ground surface temperature	Monitoring period	Number of annual observations
Alaska HWY	S Yukon N BC	-3.0	Boreal forest at low elevations shrub or alpine tundra at high elevations	Sporadic Discontinuous	10	0	2005-2018	71
Alert	High Arctic	-16.7	Polar desert	Continuous	3	0	2000-2008	14
Atlin	S Yukon N BC	1.4	Boreal white and black spruce forests at lower elevations and spruce, willow, and birch in the subalpine elevations	Sporadic Discontinuous	6	0	2011-2019	30
Baker Lake	Northern NWT & NU	-10.8	Tundra vegetation including dwarf shrubs	Continuous	1	0	2003-2008	2

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Cape Bounty	High Arctic	-14.0	Polar desert	Continuous	10	39	2011-2018	76
Carmacks	S Yukon N BC	-2.1	Boreal forest at low elevations shrub or alpine tundra at high elevations	Extensive Discontinuous	3	0	2009-2018	10
Dawson	Western Yukon	-3.8	white (*Picea glauca*) and black spruce (*Picea mariana*) forests with alpine tundra vegetation present at higher elevations	Extensive Discontinuous	15	0	2008-2021	117
Dempster	Western Yukon	-9.2	white (*Picea glauca*) and black spruce (*Picea mariana*) forests with alpine tundra vegetation present at higher elevations	Continuous	13	0	2015-2021	25
Eureka	High Arctic	-18.1	Polar desert	Continuous	6	0	2009-2013	14
Faro	Eastern Yukon	-1.9	Boreal forest at low elevations shrub or alpine tundra at high elevations	Extensive Discontinuous	12	0	2006-2009	30
Johnsons Crossing	S Yukon N BC	-0.7	Boreal forest at low elevations shrub or alpine tundra at high elevations	Sporadic Discontinuous	13	0	2006-2018	73

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Keno	Western Yukon	-2.2	Boreal forest at low elevations shrub or alpine tundra at high elevations	Extensive Discontinuous	13	0	2006-2018	48
Labrador	Labrador	-2.4 to 0.4	Coastal barrens with sparse tree cover and peatlands near the coast transitioning to open coniferous and mixed-wood upland forests	Sporadic Discontinuous	30	0	2013-2022	130
Mac Valley North	Northern NWT & NU	-9.1 to -7.0	Tundra	Continuous	1	13	1993-2012	99
Mac Valley Central	S NWT	-5.5 to -4.8	Boreal Forest with extensive peatlands	Extensive Discontinuous	4	10	1993-2012	81
Mac Valley South	S NWT	-2.3	Boreal forest with extensive peatlands	Extensive Discontinuous	3	22	1993-2012	174
North Canol	Eastern Yukon	-5.3 to -5.2	Boreal forest but transitions to alpine vegetation at higher elevations	Extensive Discontinuous	21	0	2016-2021	70
Sa Dena Hes	S Yukon N BC	-2.1	Boreal forest at low elevations shrub or alpine tundra at high elevations	Sporadic Discontinuous	12	0	2006-2009	23
Southern NWT	S NWT	-4.0 to -2.2	Patchwork of black spruce forest, mixed-wood forest, and peatlands	Sporadic Discontinuous	32	0	2015-2019	65

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Whatì	S NWT	-4.6	Patchwork of coniferous and mixed wooded forest, peat plateaus, and wetlands	Extensive Discontinuous	10	0	2019-2022	15
Whitehorse	S Yukon N BC	0.2	Boreal forest at low elevations shrub or alpine tundra at high elevations	Sporadic Discontinuous	28	0	2007-2015	133

2.2 Data Collection

Air, ground surface and ground temperature at depth measurements were recorded 1-hour to 8-hour intervals at 330 sites (Table 1). Record lengths ranged from 2-16 years. This dataset, spanning over two decades, is the product of long-term federal, territorial, and academic monitoring networks, only possible through funding and support from the Geological Survey of Canada and several Canadian universities.

Air temperature was measured ~1.5 meters above the ground surface with a Hobo U23-002 (± 0.25-0.4 °C accuracy, 0.04 °C resolution) thermistors or Vemco loggers (accuracy and precision better than 0.1 °C) housed in a radiation shield (Onset RS1). At newer sites, a Hobo U23-001 (± 0.25 °C accuracy, 0.04 °C resolution) was housed in a radiation shield. At all sites except the Southern NWT, ground surface temperature was measured 2-5 cm below the ground surface with the Hobo U23-002 internal thermistor. The Southern NWT ground surface temperatures were measured with Maxim IntegratedTM Thermochron iButton temperature loggers (model no. DS1922L; accuracy ± 0.5°C).

For most sites, ground temperature at depth was measured using the Hobo U23-002 or Hobo Pro U12-008 external thermistors, while for the remaining sites, ground temperatures at

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depth were recorded using multi-sensor cables with RBR loggers. For a majority of sites, the ground depth sensor was positioned close to or at the top of the frost table at the time of installation. For sites with multiple ground temperature observations, the sensor closest to the depth of the frost table was used. However, for some sites (n = 160 observations), annual mean ground temperature (AMGT) may not correspond to the temperature at the top of the frost table due to installation depth limitations. These sites are generally confined to coarse grained, dry, rocky sediment where the thermal gradient is typically small (Lewkowicz et al., 2012). Based on estimations of active layer or frost depth and temperature extrapolation (S1), the temperature difference between the true TTOP and the monitoring depth was generally less than 0.5 °C (n = 144 observations, average = 0.2 °C). Therefore, at these sites, AMGT was still compared directly to the modelled TTOP value.

The data was assessed for sensor drift, erroneous measurements, and missing intervals. Short data gaps (<3 consecutive days) were filled using linear interpolation, while larger gaps were flagged. Average air, ground surface and ground temperatures were only calculated for years ≥ 85% daily data completeness once erroneous values were removed and data gaps were considered.

2.3 TTOP Model Sensitivity

The TTOP model calculates equilibrium permafrost temperature using air freezing and thawing degree days, n-factors and the thermal conductivity ratio (Table 2). The TTOP model is often used spatially as the input parameters are based on widely available data commonly measured at meteorological stations (Juliussen & Humlum, 2007). However, as an equilibrium model it is not ideal for modelling transient changes in permafrost temperature and distribution.

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Additionally, the TTOP model errors are often largest near zero due to latent heat effects, which the model does not consider (Riseborough, 2007).

To assess the TTOP model sensitivity to each input parameter we first calculated baseline input parameters for the TTOP model and the reference TTOP value (TTOP model output when using values for baseline parameters derived from the measured field data) were calculated for each site.

Table 2. Variables and equations used in the TTOP sensitivity and random forest analysis. Freezing (FDD) and thawing (TDD) degree-days were calculated for air (a), ground surface (s), and ground at or close to top of permafrost (g). P is the period, usually 365 days.

Variable	Abbreviation	Equation
Temperature at Top of Permafrost (°C)	TTOP	$TTOP = \frac{(n_t * TDD_a * rk) - (n_f * FDD_a)}{P}$
Freezing Degree Days (°C days)	FDD	$FDD = \lvert\Sigma_1^P T\rvert, < 0$
Thawing Degree Days (°C days)	TDD	$TDD = \lvert\Sigma_1^P T\rvert, T > 0$
Freezing n factor	n_f	$n_f = \frac{FDD_s}{FDD_a}$
Thawing n factor	n_t	$n_t = \frac{TDD_s}{TDD_a}$
Thermal Conductivity ratio (Thawed:Frozen)	rk	$rk = \frac{FDD_s + (TDD_g - FDD_g)}{TDD_s}$
Nival Surface Offset (°C)	NVO	$NVO = \frac{FDD_a - FDD_s}{P}$
Thawing Surface Offset (°C)	TSO	$TSO = \frac{TDD_s - TDD_a}{P}$
Surface Offset (°C)	SO	$SO = MAGST - MAAT$
Thermal Offset (°C)	TO	$TO = MAGT - MAGST$

To allow for direct comparison of model sensitivity in all environments, the TTOP model equation for permafrost was utilized even for sites considered to be seasonally frozen (Way & Lewkowicz, 2018; Obu et al., 2019; Garibaldi et al., 2021). For each year and each site, FDD and

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TDD were calculated using daily average air (T_a) and ground surface temperatures (T_s) from September 1st to August 31st of the subsequent year. Freezing and thawing n-factors were then calculated for each measurement location (Table 2). The ratio of thawed to frozen thermal conductivity (rk) for sites with a deeper ground temperature measurement was calculated using FDD and TDD for both the ground surface ($_s$) and the ground temperature observation at or near the frost table ($_g$) (Table 2). For sites without a depth sensor, rk, was assigned based on vegetation class for the High Arctic and substrate for the Mackenzie Valley (n = 38) (Kersten, 1949; Gregory, 2011; Obu et al., 2019; Garibaldi et al., 2021). These sites were included even though rk needed to be assigned as they filled a substantial latitudinal gap in the dataset (Fig. S2). Using the observed thermal offset to determine rk may not necessarily be possible given the materials that are present due to potential disequilibrium. Therefore, for the purpose of this study we assume equilibrium conditions for each observation.

Once the parameters and reference TTOP values were determined, the sensitivity of the model to changes in each parameter was assessed by iteratively substituting values for one parameter while holding all other inputs constant and then calculating the TTOP temperature for each substitution. The substituted values used percentiles (minimum, 10th, 25th, 50th, 75th, 90th and maximum) calculated using the parameters across the entire study dataset. Each year of data for each site was treated as its own observation and run through the sensitivity analysis resulting in 9100 different TTOP values for each parameter. Sensitivity analysis TTOPs were then compared to the reference (i.e observed) TTOP values to assess the influence of the TTOP model to changes in each parameter.

Since vegetation is often used when assigning n-factors and rk in regions without observations, the TTOP sensitivity analysis was rerun using the median value for these

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parameters based on vegetation class and region. These TTOP outputs were then compared to the reference TTOP value for each site.

2.4 Random Forest Variable Importance Ranking

Algorithm inputs included TTOP model and additional parameters (see Table 2). Samples were randomly split into testing and training data (40% and 60% respectively both for the overall dataset and individual regions) with individual years treated as independent observations. Two random forest models were created, one using all the input variables and the other using only the TTOP model parameters (Table 3). The random forests were generated in R Studio and run using the default settings for the number of variables sampled for splitting at each node (4 and 2 for iterations 1 and 2 respectively) and number of trees (500). For each iteration, the same training and test dataset was used to ensure comparability. The Northern NWT & NU region was not included in this analysis as it had only one site with measured ground temperature at depth.

Table 3. Random forest trials including a description of variable selection, and variables used.

Random Forest Iteration	Description	Variables used
1	All Variables	FDD_a TDD_a n_f n_t rk MAAT MAGST NVO TSO SO TO FDD_s TDD_s
2	TTOP model variables	FDD_a n_f TDD_a n_t rk

Random forest provides variable importance rankings through two methods: permutation accuracy importance (mean square error (MSE) reduction) or Gini importance (Strobl et al., 2008). The former, used here, has been more widely employed in variable importance studies due to biases in Gini importance when predictor parameters vary in number and scale (Díaz-

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Uriarte & Alvarez de Andrés, 2006; Strobl et al., 2008; Grömping, 2009; Genuer et al., 2010). Reduction in MSE involves the random permutation of each variable individually to simulate its absence in the model prediction. Variable importance is then determined based on the difference in prediction accuracy before and after the permutation. Variable importance plots were created for each random forest model both for the entire dataset and for each region individually.

2.5 TTOP model performance

For sites with measured ground temperature, the performance of the TTOP model was assessed by comparing the calculated TTOP and the measured AMGT at or near the top of permafrost (observed TTOP). For the few sites where the observed AMGT was not near the top of the frost table, the observed AMGT was still compared to TTOP as the thermal offset at these sites was low (S1).

3 Results

3.1 TTOP Sensitivity

To test TTOP model sensitivity, percentile values for each parameter (calculated over the entire dataset) were directly substituted for the measured parameter value (Table 4). As the range of measured values differed for each parameter, the values and range of the substituted percentiles were also different. The potential impact of this on the interpretation of the sensitivity is discussed below.

Table 4. Substituted percentile values for each parameter replacing the measured parameter value for each iteration of this trial method. These values were determined based on the observation data.

	Minimum	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	Maximum
n_f	0	0.06	0.15	0.29	0.48	0.76	1.0

n_t	0.01	0.54	0.66	0.79	0.93	1.14	4.3
rk	0.18	0.51	0.68	0.83	0.97	1.11	1.98
FDD_a (°C days)	274	1851	2324	2857	3467	4588	7223
TDD_a (°C days)	150	727	1081	1438	1378	1944	2368

For a majority (>53 %) of sample points, changes to FDD_a, n_t, TDD_a, and rk resulted in < 1 ºC difference between the reference and perturbed TTOP output (Fig. 2b,c,d,e). However, for n_f less than half (< 27 %) remained within 1 ºC of the initial TTOP value (Fig. 2a). FDD_a showed more sensitivity than TDD_a, n_t, and rk with less than 70% of sample points remaining within 2 °C of the initial observation value (compared to > 75 %).

Latitudinal trends in sensitivity were observed with the region with the coldest permafrost (High Arctic) showing a much greater response to changes in winter parameters FDD_a and n_f) and muted response to changes in summer parameters (n_t) and the thermal conductivity ratio (rk) (Table 5, Fig. 3). However, the High Arctic region was also disproportionately sensitive to changes in TDD_a when compared to more southern regions. Moving from north to south the difference between the reference and perturbed TTOP generally increased for the thawing parameters and decreased for the freezing parameters. In the southernmost regions (Southern Yukon-Northern BC and Labrador) all parameters had similar sensitivity. All sites had the greatest sensitivity to changes in n_f or n_t and the least sensitivity to changes in FDD_a and rk. The sensitivity to rk was most similar between regions compared to the other parameters.

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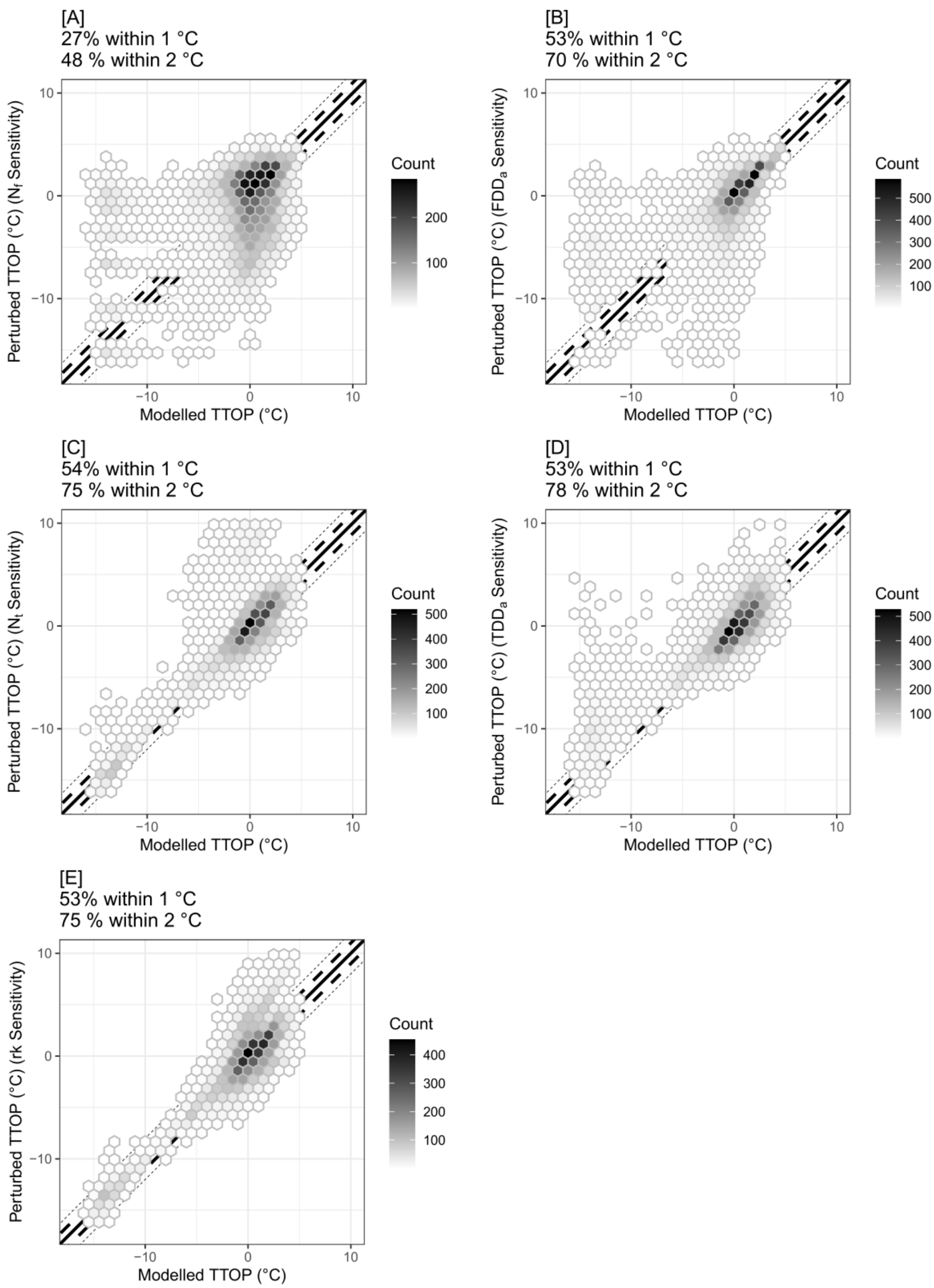

Figure 2. Reference TTOP model values compared to perturbed TTOP model values for the direct substitution of the minimum, 5th, 25th, 50th, 75th, 95th, and maximum percentile value for [A] n_f, [B] FDD_a, [C] n_t, [D] TDD_a, and [E] rk. Large dashes indicate a ± 1 °C difference while small dashes indicated a ± 2 °C difference.

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Table 5. Average absolute difference between the reference TTOP and the perturbed TTOP for each parameter within each region. Regions are High Arctic, Northern NWT & NU, Western Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern BC, and Labrador. Values followed by the same superscript letter are not significantly different (P > 0.05) between regions (along a row). Values followed by a subscript italicized letter are not significantly different (P > 0.05) within a region (down a column).

	High Arctic	**N NWT & NU**	**W Yukon**	**E Yukon**	**S NWT**	**S Yukon N BC**	**Labrador**
FDD_a (°C)	6.4	2.0_{b}^{a}	1.6_{d}^{b}	1.4_{f}^{b}	0.9^{c}	2.1_{hi}^{a}	0.9^{c}
TDD_a (°C)	3.7	1.0_{c}^{a}	1.5_{d}^{c}	1.8^{cd}	1.1^{a}	1.9_{i}^{d}	1.6_{k}^{c}
n_f (°C)	7.5	3.9	2.6_{e}^{abc}	2.4^{ad}	2.8_{g}^{c}	2.2_{hj}^{d}	2.4^{bd}
n_t (°C)	0.8_{a}	1.9_{b}^{a}	2.7_{e}^{b}	2.3^{ba}	2.7_{g}^{b}	2.3_{j}^{ab}	2.8^{b}
rk (°C)	0.7_{a}^{a}	0.8_{c}^{a}	1.5_{d}^{b}	1.3_{f}^{c}	1.6^{b}	1.4^{c}	1.6_{k}^{b}

$_{a}$ in column 2 indicates that the difference in TTOP for n_t and rk is not significantly different in the High Arctic.

^{a} in the second row indicates that the difference in TTOP for changes in FDD_a is not significantly different for the Northern NWT & NU and the Southern Yukon-Northern BC regions.

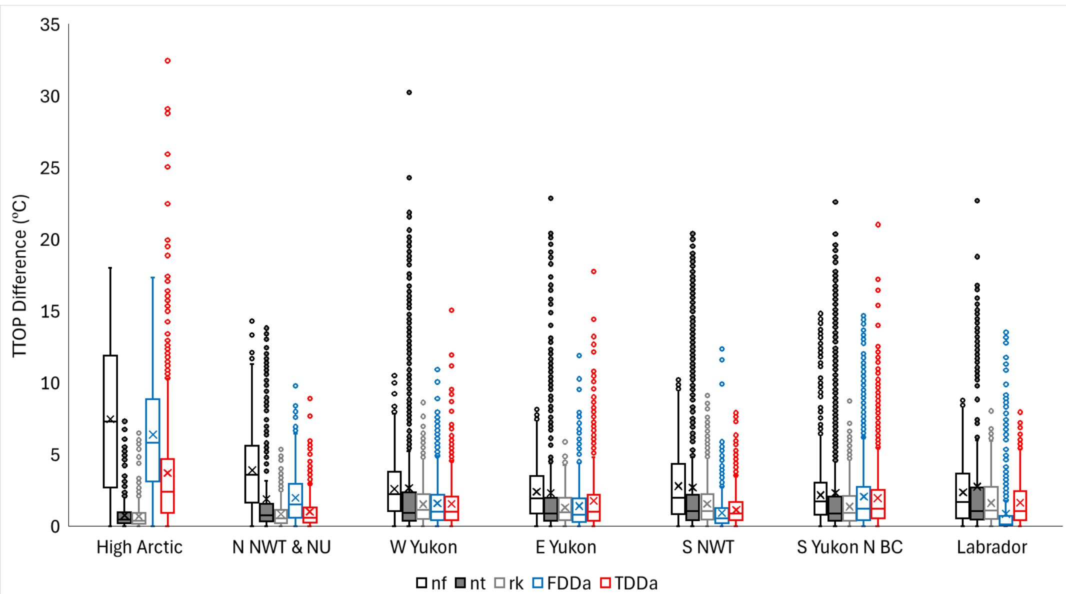

Figure 3. Boxplots for the regional absolute difference between the reference TTOP and TTOP calculated when parameters were directly substituted to a percentile value. Mean values are represented by an X, outliers are shown as circles, and the ends of the whiskers show the value for one and a half times the interquartile range. The ends of the box show the first (25 percent) and third (75 percent) quartiles and the black line within the box shows the median.

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Using the internal median parameter value (based on measured values for each landcover class within each region) resulted in a lower error than using the external median parameter value for every region and landcover class (Fig. 4). These differences were especially pronounced for n_f. For each region the shrub landcover class showed the least difference when using the internal vs. external parameters.

3.2 Random Forest

For the random forest iterations 1 and 2 (Table 3), several parameters were consistently ranked as the most and least important by virtue of the percent increase in MSE (Fig. 5). When all variables were used within the entire dataset, TO, rk and FDD_s were ranked as the most important. The least important were NVO, TSO and TDD_a. Regionally, freezing season parameters (FDD_s and n_f) and MAGST were consistently ranked as the most important parameters. Surprisingly, TDD_s was ranked as highly important only in the High Arctic and Labrador.

When using only the TTOP model parameters, n_f was ranked as the most important for every region, while n_t, rk, and TDD_a most often ranked lower in importance. TDD_a was the an most important parameter for the two southern regions and the High Arctic but was deemed to be the least important parameter for the remaining three regions. Overall, the variable importance rankings once again highlight the prominence of freezing season conditions compared to thawing.

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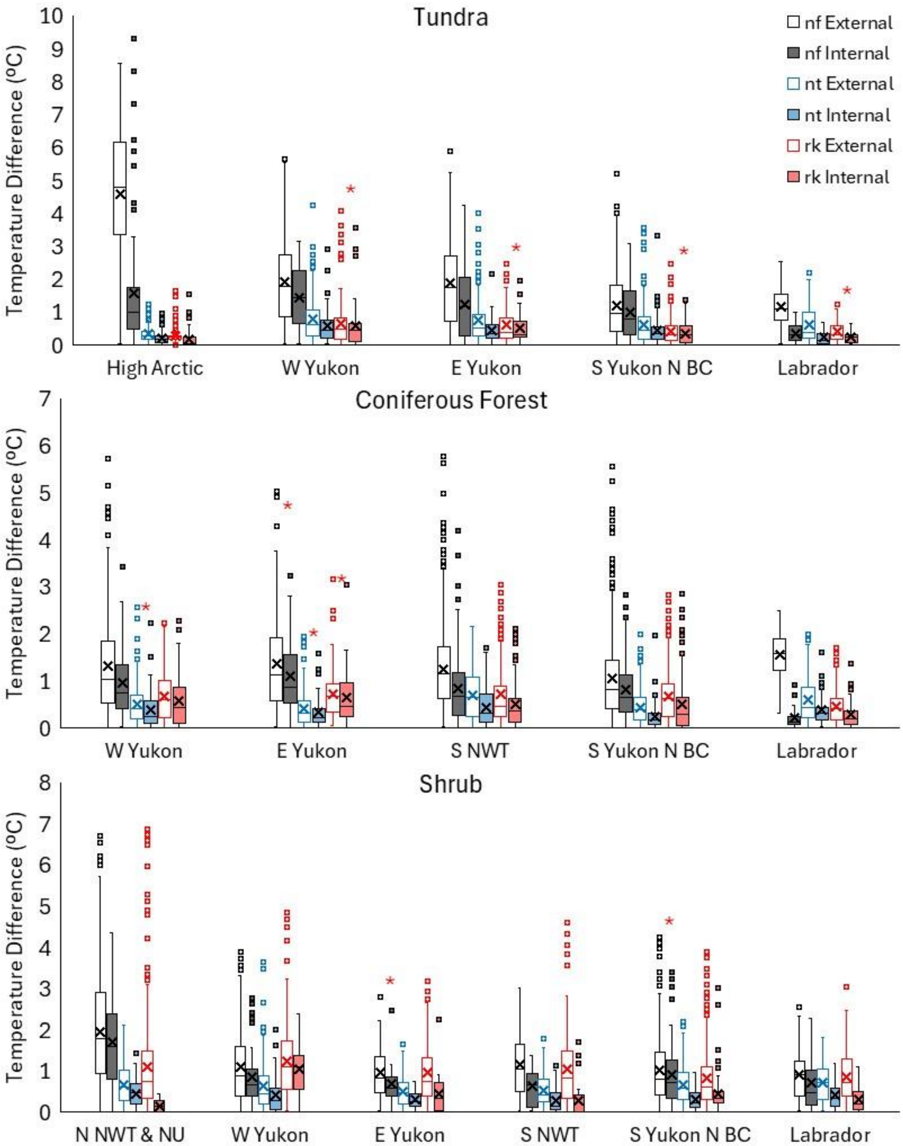

Figure 4. Boxplots for the difference between the measured ground temperature and the TTOP model using the internal parameter value (median value for the landcover type within the region) and the external parameter value (median value for the landcover type outside the region). Red asterisk (*) indicates the difference resulting from using the internal and external parameter value was not significant (P > 0.05). Mean values are represented by an X, outliers are shown as circles, and the ends of the whiskers show the value for one and a half times the interquartile range. The ends of the box show the first (25 percent) and third (75 percent) quartiles and the black line within the box shows the median.

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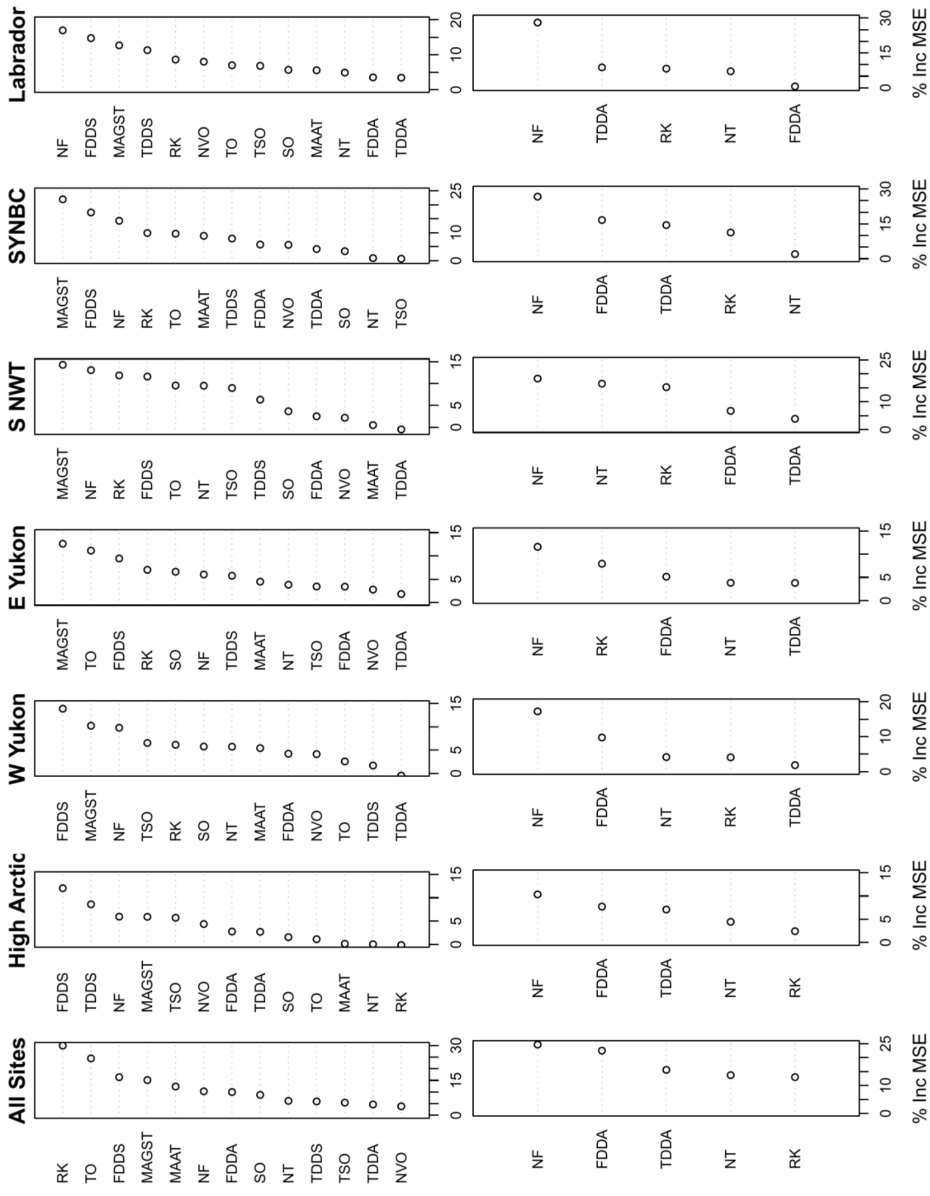

Figure 5. Variable importance plots for random forest models run using all variables (top row) or only parameters used in the standard form of the TTOP model (bottom row) for all sites and individual regions. SYNBC is the Southern Yukon-Northern BC region.

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3.3 Random Forest Variable Importance Rankings Compared to TTOP Sensitivity Results

The variable importance conclusions from the TTOP sensitivity and random forest using only the TTOP parameters did not match perfectly, but there were commonalities for certain parameters. Both analyses highlighted the importance of the freezing parameters (especially n_f). Three regions (High Arctic, Southern NWT, and Labrador) showed similarity in parameter importance between the two methods. The remaining regions showed greater discrepancies, particularly in the rankings of n_t and rk. Despite the differences between the two analyses, both methods generally captured the trends in the overall and regional differences in parameter importance.

3.4 TTOP Model Performance

The TTOP model performed well compared to the observed AMGT overall with an RMSE of 0.2 ºC, but with regional differences in model performance (Fig. 6). Model error was low in most regions, except for the High Arctic. However, the Southern NWT and Southern Yukon-Northern BC regions included a number of outliers with large errors. Additionally, the model only misclassified permafrost presence or absence at 3 of the 612 observations. Two of the three observations were in the Southern Yukon-Northern BC region both of which were false positives for permafrost (no permafrost in observation but negative modelled temperature). The third observation was in the SNWT region where permafrost was observed but the model indicated its absence.

https://doi.org/10.5194/egusphere-2025-4478
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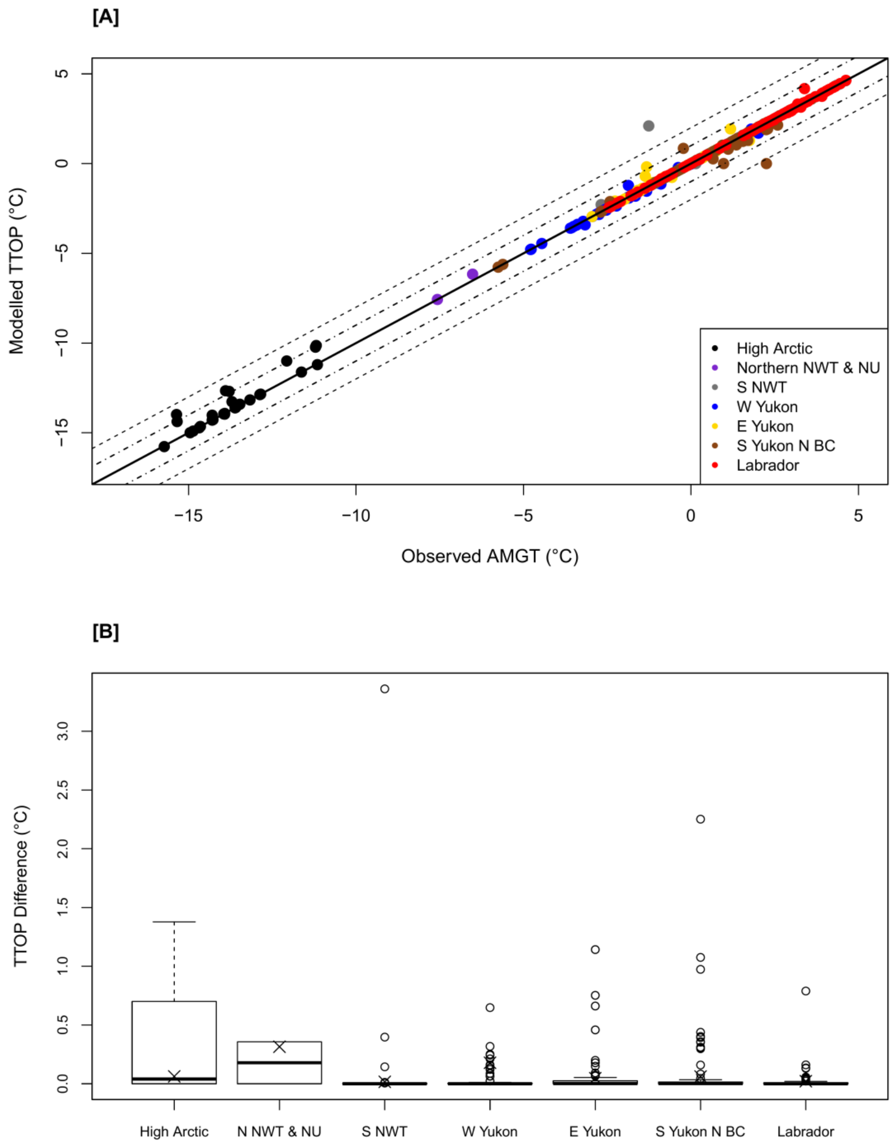

Figure 6. A) Comparison of TTOP model outputs to the measured annual mean ground temperature (AMGT). The solid line in panel A is the 1:1 relation between modelled and observed while the dashed lines indicate 1 and 2 ºC differences. **B)** Boxplots for the absolute difference between the modelled TTOP and the measured AMGT close to the frost table across the entire study area and for individual regions. Mean values are represented by an X, outliers are shown as circles, and the ends of the whiskers show the value for one and a half times the interquartile range. The ends of the box show the first (25 percent) and third (75 percent) quartiles and the black line within the box shows the median.

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4 Discussion

4.1 TTOP Model Parameter Sensitivity

The sensitivity of the TTOP model to changes in specific parameters is affected by the structure of the model and the values of the parameters. The model across all regions was most sensitive to changes in n_f, due to the higher number of FDD_a (compared to TDD_a), which amplified the response to changes (Smith & Riseborough, 1996, 2002; Bevington & Lewkowicz, 2015). Regionally, the sensitivity of the model to changes in the thawing parameters, especially TDD_a and n_t increased southward as the difference between FDD_a and TDD_a decreased. The exception to this was the High Arctic, where the model was disproportionately sensitive to changes in TDD_a despite the large contrast in the number of FDD_a and TDD_a in this region (up to five times as many FDD_a as TDD_a). The increased sensitivity to changes in TDD_a likely results from the high values of n_t and rk, with values regularly approaching or exceeding 1.0. As a result, changes in TDD_a were amplified in this region. This also highlights the vulnerability of this region to changes in climate due to the lack of vegetation increasing the importance and influence of MAAT on the ground thermal regime compared to other regions with more well-developed surface cover (Shur & Jorgenson, 2007; Throop et al., 2012; Smith et al., 2022).

It is also important to note this study perturbed TTOP model parameters using the entire measured dataset. Therefore, sensitivity to certain parameters may be higher than for studies with altered parameters based on values measured within a region which may have limited variability (Way & Lewkowicz, 2018). As a result, our results may highlight relatively higher sensitivity for different parameters such as n_t compared to n_f in Labrador (Way & Lewkowicz, 2018).

The sensitivity analysis also showed that TTOP model parameters are not necessarily transferable between regions with the same landcover class. This is especially true for n_f and n_t as

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using the median values for the same landcover class, but an external region resulted in a significantly greater error than utilized the median value corresponding to the site region. This could be a result of the large range of environments sampled in this analysis as previous studies have shown transferability of n_t between rock and forest landcovers of Labrador and Southern Yukon (Way & Lewkowicz, 2018). However, utilizing n_f from Southern Yukon in Labrador increased TTOP model errors (Way & Lewkowicz, 2016), which supports our findings. Rk appears to be generally more transferable, especially for the limited number of tundra sites which might be the result of restricted soil (and organic) development and moisture in this landcover (Throop et al., 2012). Additionally, rk may have a smaller influence on ground temperature in certain environments (Karjalainen et al., 2019) and therefore the importance (or lack of transferability) may be masked by the large dataset. These results demonstrate the need for caution in assuming the regional transferability of parameters, especially in environments where values may differ substantially.

4.2 Random Forest Variable Importance Rankings

The variable importance rankings for the overall and regional datasets were a product of differences in values of the measured field inputs. TO and rk were ranked as the most important parameters when all variables were used. TO has previously been suggested as the most important parameter for determining the southern extent of permafrost, under equilibrium conditions, as a high TO can protect permafrost from higher air temperatures (Smith & Riseborough, 2002). However, neither were ranked as the most important parameters in any of the regional analyses. TO and rk had lower correlation with the other parameters, which may have artificially elevated their importance, but they are correlated with each other which may explain why both have elevated importance.

NVO has also been highlighted in the literature as an important parameter, determining the northern and southern limit of discontinuous permafrost and influencing permafrost existence within the discontinuous zone (Nicholson & Granberg, 1973; Smith & Riseborough, 2002). However, in this study NVO ranked as middle to low importance overall and for every region, even those spanning the continuous to discontinuous permafrost transition. Finally, overall and regionally, MAGST was deemed to be an important parameter for accurate predictions of MAGT. While this may be true for sites with a negligible thermal offset (Lou et al., 2019; Garibaldi et al., 2021), MAGST alone cannot accurately predict the thermal state of permafrost without additional information on the thermal properties, especially at sites with larger thermal offsets (James et al., 2013; Guo et al., 2024; Brown & Gruber, 2025) . Therefore, the elevated importance of this parameter may indicate that sites with small thermal offsets are over-represented in the dataset (Fig. S3c).

4.3 TTOP model performance

The TTOP model generally performed well compared to observed AMGT, resulting in minimal errors in predicted TTOP even seasonally frozen sites. The RMSE for the TTOP model for this study was similar to or smaller than those from previous TTOP modelling results in the same region (Obu et al., 2019; Garibaldi et al., 2021). This is likely a product of the use of directly measured and calculated input parameters rather than the characterization of parameters from environmental variables such as vegetation or spatial interpolation. This highlights the importance of *in situ* data for validation of parameters for accurate predictions of permafrost and ground temperatures.

The TTOP model did not perform as well in the High Arctic for certain observations, especially those from Cape Bounty during 2016-2017, when the predicted TTOP was higher than the observed values. The AMGST for 2016-2017 was substantially higher than those from the previous years. Although the AMAT showed only a slight deviation, n_f at these sites decreased substantially, indicating greater snow depths. As a result, the TTOP model parameters were not in equilibrium with ground temperature for this year, yielding a larger discrepancy.

The TTOP model using measured parameters performed surprisingly well in locations of warmer, more marginal permafrost or locations with seasonal frost, despite these locations potentially being in disequilibrium with the current climate. However, these regions, especially the Southern NWT and Southern Yukon-Northern BC, also included individual sites with the largest errors (Fig. 6a) showing a lack of consistency in model performance. These results may indicate sites with more ecosystem-protected permafrost and high apparent TOs or disequilibrium conditions (Shur & Jorgenson, 2007; James et al., 2013; Vegter et al., 2024). It should be noted that even small temperature errors can result in the misclassification of permafrost presence where ground temperatures are close to 0 °C (Daly et al., 2022; Vegter et al., 2024) whereas the classification would be unaffected even with a larger temperature error in the High Arctic. However, the model accurately predicted permafrost presence or absence for the vast majority of observations (> 98 %) in this study even though 38% of observations were within -1 °C to +1 °C.

4.4 Sources of Uncertainty

The methods used to rank the importance of variables have their own uncertainties that could affect the reliability of the results. First, since the percentiles were derived from the observed data the range of values for each parameter differed and would vary if a different dataset was used. Second, although random forest is able to cope with highly correlated variables

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for prediction (Boulesteix et al., 2012), there are conflicting conclusions on the reliability of variable importance rankings (Strobl & Zeileis, 2008; Nicodemus et al., 2010; Tolosi & Lengauer, 2011; Gregorutti et al., 2017). For this study, a majority of the input parameters are highly correlated with at least one other parameter as some parameters are used to derive others. This may have led the variable importance rankings of the random forest to be unreliable when all parameters where used. Additionally, although the random forest model using all variables performed relatively well (MSE 0.2 °C; variance explained 98%), the regional models had lower percentages of variance explained (43 - 93 %) even though MSE was similar (0.2 – 0.8 °C). This may have impacted the reliability of the variable importance rankings for these models, as they may have accurately predicted ground temperature. Despite the possible errors and uncertainty in the results of this, the variable importance analyses were in general agreement for the two methods and supported findings from previous studies.

Variation in variable importance rankings between the two methods may also have resulted from the difference in approaches. As the TTOP model utilized multiplicative factors, the importance of the parameters was elevated by nature of the model equation. The random forest variable importance ranking was not dependent on this equation and as a result, the importance was potentially different based on the predictive method alone. Additionally, the TTOP model sensitivity analysis was determined through perturbation of the model parameters, thereby ranking the parameters' importance based on the response. Contrastingly, the random forest variable importance ranking was determined based on the current thermal conditions. This may also have resulted in some discrepancy in the rankings. However, both methods showed similar rankings and regional trends overall.

4.5 Parameter classification recommendations

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Since the TTOP model was deemed more sensitive to certain model parameters in the entire dataset and in certain regions, accurate parameterization of the most important variables for the study location is vital. Overall, the freezing season parameters were generally deemed the most important; therefore, adequate characterization is essential for accurate predictions of TTOP at national or circumpolar scales. This is especially true for n_f which is typically the most difficult to parameterize since it is dependent on a wide range of conditions including timing, depth, and morphology of snow and substrate conditions including soil moisture and is not necessarily transferable between regions (Smith & Riseborough, 2002; Zhang, 2005;Throop et al., 2012; Way & Lewkowicz, 2016).

Regionally, in locations where $FDD_a >> TDD_a$, the impact of inadequate characterization of n_t, rk, and was shown to be minimal. Therefore, more general assumptions and classifications will not result in a substantial increase in uncertainty and greater focus should be put on accurate characterization of FDD_a and n_f. In locations where FDD_a and TDD_a are similar (i.e., AMAT is close to 0°C), the sensitivity of the model to changes in thawing parameters is elevated and accurate characterization of n_t and rk becomes more important. For several continental and circumpolar modelling studies, a uniform value of 1.0 was utilized as the input for n_t across the study area (Henry & Smith, 2001; Obu et al., 2019). While this assumption is unlikely to increase uncertainty in areas above treeline and tundra it is likely to result in errors in boreal forested areas due to the elevated importance of n_t in this landcover. Additionally, n_f and to some extent n_t varied regionally even within the same landcover type due to microclimatic differences, vegetation and wind exposure, which influence both summer and winter conditions (Smith & Riseborough, 2002). As such regional transferability of these parameters between regions may be limited especially over large geographic and climatological gradients.

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Finally, many studies that determine TTOP characterize rk using vegetation, assigning values between 0.0 and 1.0 (Smith & Riseborough, 1996; Riseborough & Smith, 1998; Way & Lewkowicz, 2016; Obu et al., 2019; Garibaldi et al., 2021). However, recent studies (including the data analyzed for this study) have shown rk values exceeding 1.0 (Bevington & Lewkowicz, 2015; Lin et al., 2015; Zou et al., 2017). This likely occurs as a product of extremely dry conditions in winter and higher soil moisture during summer, resulting in greater thermal conductivity in the warm season. This is typically observed at sites with rocky or bedrock substrates and limited vegetation cover and soil moisture (Lin et al., 2015; Luo et al., 2018). In southern permafrost environments, the assumption of rk < 1 at these sites (such as high elevation rocky slopes, Fig. 2b) likely results in mischaracterization of the permafrost condition. The varying sensitivity of the TTOP model to specific parameters in different environments demonstrates the need for accurate parameterization and validation of TTOP model parameters to ensure valid outputs. This highlights the need for *in situ* data parameter to increase the accuracy of future TTOP modelling studies to validate remotely-derived parameter values.

5 Conclusions

The results of this analysis highlight the overall sensitivity of the TTOP model to changes in the freezing parameters (n_f and FDD_a) compared to the response to changes in the thawing parameters (n_t, TDD_a) and rk. Across all sites, regions, and perturbation methods, the model was most sensitive to changes in n_f with 73 % of TTOP outputs changing by at least 1 ºC from the original TTOP value followed by FDD_a at 30 % changing by at least 2 °C. The model was least sensitive to changes in TDD_a with only 22 % of TTOP model outputs exceeding 2 ºC difference from the reference TTOP value, followed by n_t and rk at 25 %. Differing sensitivity patterns emerged regionally, mainly showing the diminishing response to changes in n_f and the increasing

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response to changes in TDD_a, n_t, and rk at more southerly sites, although sensitivity to changes in n_f remained high.

The random forest variable importance rankings also highlighted the importance of the freezing season parameters using both a wide variety of temperature parameters and only those used in the standard form of the TTOP model. The increasing importance of the thawing and annual parameters moving south was also shown. Although the random forest variable importance rankings showed some differences from the TTOP sensitivity results, potentially due to high correlation between variables, they indicated similar regional trends in variable importance.

The results of this study highlight the importance of correct parameterization, specifically of the freezing parameters in small-scale national or circumpolar modelling studies, and the increased importance of parameterization of the thawing parameters in locations where the magnitude of FDD_a and TDD_a are similar. Although these conclusions had been theorized, a robust network of *in situ* data provided essential empirical support. Ultimately, the findings of this study will help future modelling studies determine parametrization allocation effort based on location and scale and may help explain sources of error and uncertainty in modelled results.

Data Availability

Data will be made available upon request to corresponding author (madeleinegaribaldi9(@gmail.com)

Author Contributions

MCG – Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Visualization, Writing (original draft preparation)

PPB – Conceptualization, Funding Acquisition, Investigation, Methodology, Supervision, Writing (review and editing)

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AB – Conceptualization, Investigation, Methodology, Writing (review and editing)

SLS – Funding Acquisition, Investigation, Writing (review and editing)

SFL – Funding Acquisition, Investigation, Writing (review and editing)

JEH – Data Curation, Investigation, Writing (review and editing)

AGL – Conceptualization, Funding Acquisition, Investigation, Methodology, Writing (review and editing)

HA – Data Curation, Writing (review and editing)

Competing Interests

The authors declare they have no competing interests

Acknowledgements

We acknowledge sites used in this research are located on the Akaitcho, Dehcho, Dënéndeh, Gwich'in, Gwich'in Nành, Hän, Inuit Nunangat, Inuvialuit, Kaska Dena Kayeh, Kluane, Kwanlin Dün, Metis, Na-cho Nyak Dun, Nitassinan, NunatuKavut, Nunatsiavut, Sahtu, Shita Got'ine, Tagé Cho Hudän, Tagish, Taku River Tlingit, Teslin Tlingit Council, Tr'ondëk Hwëch'in, Tłı̨chǫ Ndè, Vunlut Gwich'in settlement regions and traditional territories. Funding for this paper was provided by the Natural Science and Engineering Research Council, the Northern Scientific Training Program, Polar Knowledge Canada, Natural Resources Canada, Government of the Northwest Territories, W. Garfield Weston Foundation, the Royal Canadian Geographical Society, the University of Ottawa, and the University of Lethbridge. Logistic support was provided by Polar Continental Shelf Program, and Inuvik Research Institute. Data collection at Alert would not be possible without support from Environment and Climate Change Canada and Department of National Defence. We would also like to thank the numerous colleagues who have contributed to data collection over the years. Finally, we would like to thank HB O'Neill for review before submission.

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