

1 **Determining TTOP model parameter importance and overall performance across northern**
2 **Canada**

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30 Abstract

31 Modelling current permafrost distribution and response to a ~~warming~~changing climate
32 depends on understanding which factors most strongly control ground temperatures. The
33 Temperature at the Top of Permafrost (TTOP) model provides ~~a simple, widely used~~an analytical
34 framework for estimating permafrost presence and thermal state, yet its sensitivity to key
35 parameters remains poorly quantified across diverse northern environments. This study evaluates
36 the relative influence of TTOP model parameters using ground and air temperature data from
37 330 sites across northern Canada. A leave - one - out cross-validation approach to determine
38 model sensitivity was combined with random forest analysis ~~was used to assess both model~~
39 ~~sensitivity and to rank~~ variable importance. Results show that TTOP performance is dominated
40 by freezing-season conditions—particularly the freezing n-factor and freezing degree days—
41 while thaw-season parameters exert less control. Sensitivity ~~patterns vary~~varies by region, with
42 thawing parameters becoming more influential where the duration of the freezing and thawing
43 seasons is similar. Machine-learning results highlight~~also highlighted~~ the ~~additional~~ importance
44 of thermal offset and mean surface temperatures, ~~emphasizing the importance of~~ which are
45 strongly influenced by substrate properties. While the model generally reproduces observed
46 ground temperatures well, (RMSE of 0.2 °C), parameters derived from landcover classes were
47 not transferable between sites, underscoring the importance of locally calibrated inputs. Overall,
48 this study ~~clarifies~~is the first empirically-based Canada-wide assessment of how different
49 climatic and environmental factors ~~shape~~affect the accuracy of permafrost temperature modelling
50 and provides practical guidance for improving parameterization in regional and global
51 permafrost models.

52 1 Introduction

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

59 The Temperature at Top of Permafrost (TTOP) model (~~Table 2~~) (Riseborough & Smith,
60 1998) has been used to estimate permafrost temperature and presence at continental to local
61 scales (Henry & Smith, 2001; Gislén et al., 2013; Way & Lewkowicz, 2016; Obu et al., 2019;
62 Vegter et al., 2024) and in a variety of permafrost environments including in the High Arctic and
63 in mountains (Bevington & Lewkowicz, 2015; Garibaldi et al., 2021; Garibaldi et al., 2024). Its
64 extensive use for spatial modelling is principally ~~due to its simplicity compared to many~~
65 ~~numerical models, as well as using~~ because it requires fewer input ~~data that are generally~~
66 ~~measured by site condition and~~ meteorological ~~stations~~ variables than more complex one-
67 dimensional numerical or surface energy balance models. It ~~is~~ has also ~~directly been shown to be~~
68 transferable to a variety of permafrost environments without the need for extensive recalibration
69 ~~as with~~ unlike empirical-statistical models (Juliussen & Humlum, 2007; Riseborough et al.,
70 2008). ~~A of the~~ The primary challenge of using the TTOP ~~model, however, is determining the~~
71 ~~values~~ modelling approach is parameterization of the scaling factors (n-factors) and soil thermal
72 conductivities ~~used for model parameterization~~ (Juliussen & Humlum, 2007). In modelling
73 studies, these scaling factors ~~are~~ have typically been assigned based on landcover class or
74 topographic class using field measurements or values presented in the literature (Riseborough et
75 al., 2008; Gislén et al., 2013; Obu et al., 2019). Few studies, ~~however,~~ have examined the

76 uncertainties arising from mischaracterization of the ~~value of the~~ TTOP model ~~parameters on the~~
77 ~~TTOP model output~~ parameter values or the relative importance of each parameter which may
78 vary substantially in different permafrost environments (Riseborough, 2004; Way & Lewkowicz,
79 2018).

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

94 TTOP parameters are also evaluated using a machine learning approach (random forest).
95 Random forest is a supervised machine learning technique, which combines randomized decision
96 trees with bagging, and aggregates their predictions through averaging or majority vote (Breiman
97 2001; Biau & Scornet, 2016). Random forest ~~has been used in studies of air quality (Yu et al.,~~
98 ~~2016; Pendergrass et al., 2022), chemoinformatics (Mitchell, 2014), ecology (Cutler et al., 2007;~~

99 ~~Brieue et al., 2018)~~ and remote sensing (Belgiu & Drăgu, 2016). Recently, random forest has
100 ~~been used in spatial mapping of permafrost presence using environmental predictors~~
101 ~~(topography, rock glaciers, vegetation, and land surface characteristics) in a variety of~~
102 ~~environments (Pastiek et al., 2015; Deluigi et al., 2017; Baral & Haq, 2020). Random forest also~~
103 ~~provides~~ also allows determination of variable importance rankings which can be used to either
104 identify important variables for explanatory or interpolation purposes or to identify a small
105 number of variables that provide a good prediction (Díaz-Uriarte & Alvarez de Andrés, 2006;
106 Grömping, 2009; Genuer et al., 2010). In permafrost environments, these importance rankings
107 have been ~~analyzed for~~ applied in analysis of snow depth and landslide potential ~~but have yet to~~
108 ~~be thoroughly investigated for thermal parameters~~ (Behnia & Blais-Stevens, 2018; Meloche et
109 al., 2022). ~~As the expanded use-~~ and have begun to be applied to analysis of ground surface
110 temperatures at a regional scale (Colyn et al., 2025). Continued adoption of machine learning
111 ~~parameterization in conjunction with-~~ based approaches to permafrost science and potential
112 expansion of its use in parameterizing process-based models ~~may be an important next step for~~
113 ~~permafrost modelling studies, it is important to understand the variation in variable importance~~
114 ~~for permafrost temperature~~ highlights the need to improve our understanding of how these models
115 perform with real-world field data collected from across a variety of environments.

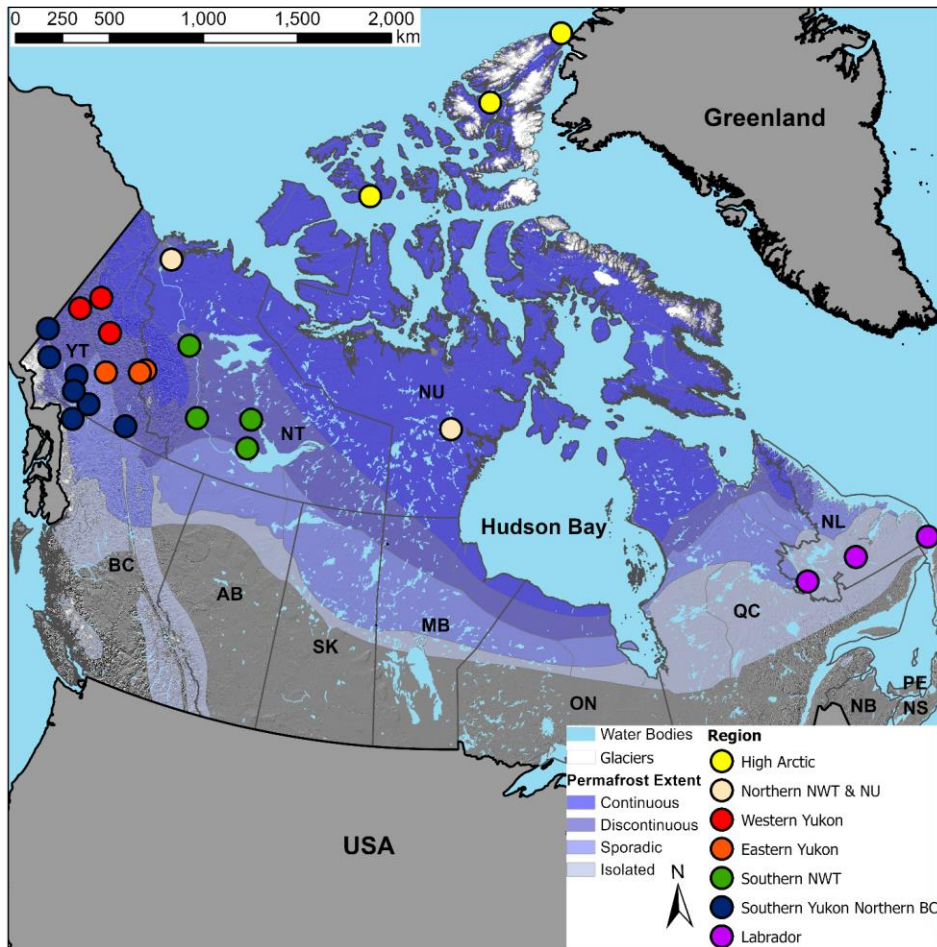
116 The objectives of this study are: (1) to ~~analyze these both a~~ sensitivity of the analysis and
117 machine learning (random forest) to evaluate TTOP model ~~to incremental changes in~~ parameter
118 ~~value; (2) to test the utility of machine learning for evaluating TTOP model variable~~ importance;
119 using field observations and ~~(3)~~ (2) to assess the accuracy of the TTOP model using measured
120 parameters across permafrost regions of Canada. ~~The~~ These results ~~should guide~~ will support

121 future efforts to improve TTOP model parameter calculations and to assess the performance of
122 the TTOP model across differing environments.

123 **2 Methods**

124 **2.1 Study Area**

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



128
 129 **Figure 1.** Study area map showing the general location of the study sites used in the TTOP
 130 sensitivity analysis and random forest. The sites were grouped into seven regions for analysis
 131 (indicated by colour): High Arctic (Queen Elizabeth Islands), Northern NWT & NU, Western
 132 Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern British Columbia, and
 133 Labrador. Permafrost extent from Brown et al. (2002). Contains information licenced under the
 134 Open Government Licence – Canada.

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

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

140 **Table 1.** Environmental and sampling details for each study area including permafrost condition,
 141 mean annual air temperature (MAAT) for the 1991-2020 climate normal from closest EC station
 142 (if available), vegetation characteristics, number of sampling locations and length of monitoring
 143 period. Total number of observations is the number of individual years of data for each site in the
 144 region. (Stanek et al., 1980; Heginbottom et al., 1995; Aylsworth & Kettles, 2000; Smith et al.,
 145 2009b; Gregory, 2011; Medeiros et al., 2012; Bevington & Lewkowicz, 2015; Duchesne et al.,
 146 2015; Holloway, 2020; Daly et al., 2022; Environment and Climate Change Canada, 2021;
 147 Lewkowicz, 2021; Ackerman, 2022; [Garibaldi; Tutton et al., 2021](#); [Garibaldi et al., 2024a](#);
 148 [Garibaldi et al., 2024b](#); [Forget et al., 2024](#); 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
Adlin	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
Cape Bounty	High Arctic	-14.0	Polar desert	Continuous	10	39	2011-2018	76

Mac Valley North	Labrador	Keno	Johnsons Crossing	Faro	Eureka	Dempster	Dawson	Carmacks
Northern NWT & NU	Labrador	Western Yukon	S Yukon N BC	Eastern Yukon	High Arctic	Western Yukon	Western Yukon	S Yukon N BC
-9.1 to -7.0	-2.4 to 0.4	-2.2	-0.7	-1.9	-18.1	-9.2	-3.8	-2.1
Tundra	Coastal barrens with sparse tree cover and peatlands near the coast transitioning to open coniferous and mixed-wood upland forests	Boreal forest at low elevations shrub or alpine tundra at high elevations	Boreal forest at low elevations shrub or alpine tundra at high elevations	Boreal forest at low elevations shrub or alpine tundra at high elevations	Polar desert	white (<i>Picea glauca</i>) and black spruce (<i>Picea mariana</i>) forests with alpine tundra vegetation	white (<i>Picea glauca</i>) and black spruce (<i>Picea mariana</i>) forests with alpine tundra vegetation present at higher elevations	Boreal forest at low elevations shrub or alpine tundra at high elevations
Continuous	Sporadic Discontinuous	Extensive Discontinuous	Sporadic Discontinuous	Extensive Discontinuous	Continuous	Continuous	Extensive Discontinuous	Extensive Discontinuous
1	30	13	13	12	6	13	15	3
13	0	0	0	0	0	0	0	0
1993-2012	2013-2022	2006-2018	2006-2018	2006-2009	2009-2013	2015-2021	2008-2021	2009-2018
99	130	48	73	30	14	25	117	10

Whitehorse	Whati	Southern NWT	Sa Dena Hes	North Canol	Mac Valley South	Mac Valley Central
S Yukon N BC	S NWT	S NWT	S Yukon N BC	Eastern Yukon	S NWT	S NWT
0.2	-4.6	-4.0 to -2.2	-2.1	-5.3 to -5.2	-2.3	-5.5 to -4.8
Boreal forest at low elevations shrub or alpine tundra at high elevations	Patchwork of coniferous and mixed wooded forest, peat plateaus, and wetlands	Patchwork of black spruce forest, mixed-wood forest, and peatlands	Boreal forest at low elevations shrub or alpine tundra at high elevations	Boreal forest but transitions to alpine vegetation at higher elevations	Boreal forest with extensive peatlands	Boreal Forest with extensive peatlands
Sporadic Discontinuous	Extensive Discontinuous	Sporadic Discontinuous	Sporadic Discontinuous	Extensive Discontinuous	Extensive Discontinuous	Extensive Discontinuous
28	10	32	12	21	3	4
0	0	0	0	0	22	10
2007-2015	2019-2022	2015-2019	2006-2009	2016-2021	1993-2012	1993-2012
133	15	65	23	70	174	81

149

150 **2.2 Data Collection**

151 Air, ground surface and ground temperature at depth measurements were recorded at 1-
152 hour to 8-hour intervals at 330 sites (Table 1). Record lengths ranged from 2-16 years. This
153 dataset, spanning over two decades, is the product of long-term federal, territorial, and academic

154 monitoring networks, only possible through funding and support from the Geological Survey of
155 Canada and several Canadian universities.

156 Air ~~temperature was~~temperatures were generally measured ~1.5 to ~2 meters above the
157 ground surface with ~~an~~ Onset Hobo U23-002 (± 0.25 - 0.4 °C accuracy, 0.04 °C resolution)
158 thermistors or Vemco loggers (accuracy and precision ~~better than~~ 0.1 °C) (previously owned by
159 AMIRIX Systems Inc.) housed in a radiation shield (Onset RS1). At newer sites, a Hobo U23-
160 001 (± 0.25 °C accuracy, 0.04 °C resolution) was housed in a radiation shield. At all sites except
161 the Southern NWT, ground surface temperature was measured 2-5 cm below the ground surface
162 with the Hobo U23-002 internal thermistor. The slight difference in surface sampling depth (~ 3
163 cm) did not have an impact on the results as the temperature difference is outside the logger
164 accuracy. The Southern NWT ground surface temperatures were measured with Maxim
165 ~~Integrated™~~Integrated TM Thermochron iButton temperature loggers (model no. DS1922L;
166 accuracy ± 0.5 °C).

167 For most sites, ground temperature at depth was measured using the Hobo U23-002 or
168 Hobo Pro U12-008 external thermistors, while for the remaining sites, ground temperatures at
169 depth were recorded using multi-sensor cables with RBR loggers. For a majority of sites, the
170 ground depth sensor was positioned close to or at the top of the frost table at the time of
171 installation. For sites with multiple ground temperature observations, the sensor closest to the
172 depth of the frost table was used. However, for ~~some sites (n=160)~~ less than a quarter of
173 observations, (23%), annual mean ground temperature (AMGT) may not correspond to the
174 temperature at the top of the frost table due to installation depth limitations. These sites are
175 generally confined to coarse grained, dry, rocky sediment where the thermal gradient is typically
176 small (Lewkowicz et al., 2012). Based on estimations of active layer or frost depth and

177 temperature extrapolation (S1), the ~~temperature~~ difference between the true TTOP and the
178 ~~temperature at the~~ monitoring depth was generally less than 0.5 °C (~~n=14490 %~~ observations,
179 average = 0.2 °C). Therefore, at these sites, AMGT was still compared directly to the modelled
180 TTOP value.

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

186 2.3 TTOP Model Sensitivity

187 The TTOP model calculates equilibrium permafrost temperature using air freezing and
188 thawing degree days, n-factors and the thermal conductivity ratio (Table 2). The TTOP model is
189 often used spatially as the ~~meteorological~~ input parameters are ~~based on widely available data~~
190 commonly ~~measured at~~ ~~able to be estimated from~~ meteorological stations (Juliussen & Humlum,
191 2007). However, as an equilibrium model ~~it~~, TTOP is not ideal for modelling transient changes
192 in permafrost temperature and distribution. ~~Additionally, the~~ TTOP model errors are often largest
193 near ~~zero~~0°C due to latent heat effects, which the model does not consider (Riseborough, 2007).

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

198 **Table 2.** Variables and equations used in the TTOP sensitivity and random forest analysis.
 199 Freezing (FDD) and thawing (TDD) degree-days were calculated for air (a), ground surface (s),
 200 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	$FDD = \sum_1^P T , < 0$
Thawing Degree Days (°C days)	TDD	$TDD = \sum_1^P T , T > 0$
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	$TO = MAGT - MAGST$

201

202 To allow for direct comparison of model sensitivity in all environments with measured data, the
 203 TTOP model equation for permafrost was utilized even for also applied to sites considered to be
 204 seasonally frozen (Way & Lewkowicz, 2018; Obu et al., 2019; Garibaldi et al., 2021). For each
 205 year and each site, FDD and TDD were calculated using daily average air (T_a) and ground
 206 surface temperatures (T_s) from September 1st to August 31st of the subsequent year. Freezing
 207 and thawing n-factors were then calculated for each measurement location (Table 2). The ratio of
 208 thawed to frozen thermal conductivity (rk) for sites with a deeper ground temperature
 209 measurement was calculated using FDD and TDD for both the ground surface (s) and the ground
 210 temperature observation at or near the frost table (g) (Table 2). For sites without a depth sensor,
 211 rk, was assigned based on vegetation class for the High Arctic and substrate for the Mackenzie

212 Valley (n = 38) (Kersten, 1949; Gregory, 2011; Obu et al., 2019; Garibaldi et al., 2021). These
213 sites were included even though rk needed to be assigned as they filled a substantial latitudinal
214 gap in the dataset (Fig. S2). Using the observed thermal offset to determine rk may not
215 necessarily be possible given the materials that are present due to potential disequilibrium.
216 ~~Therefore~~However, for the ~~purpose~~purposes of this study we ~~assume~~assumed equilibrium
217 conditions for each observation.

218 Once the parameters and reference TTOP values were determined, the sensitivity of the
219 model to changes in each parameter was assessed by iteratively substituting values for one
220 parameter while holding all other inputs constant and then calculating the TTOP
221 ~~temperature value~~ for each substitution. The substituted values used percentiles (minimum, 10th,
222 25th, 50th, 75th, 90th and maximum) calculated using the parameters across the entire study
223 dataset. We selected percentile-based substitution to test TTOP Model sensitivity as it allowed us
224 to increase and decrease parameter values within observed ranges while avoiding introducing
225 negative values. Additionally, percentile substitution allows for a direct comparison of sensitivity
226 to each parameter across regions as the parameters at all sites were changed to the same value.
227 Each year of data for each site was treated as its own observation and run through the sensitivity
228 analysis resulting in 9100 different TTOP values for each parameter. Sensitivity analysis TTOPs
229 were then compared to the reference (i.e observed) TTOP values to assess the influence of the
230 TTOP model to changes in each parameter.

231 Since vegetation is often used when assigning n-factors and rk in regions without
232 observations, the TTOP sensitivity analysis was ~~rerun~~re-run using the median value for these
233 parameters based on vegetation class and region. These TTOP outputs were then compared to the
234 reference TTOP value for each site.

235 **2.4 Random Forest Variable Importance Ranking**

236 Algorithm inputs included TTOP model and additional parameters (see Table 2). Samples
 237 were randomly split into testing and training data (40% and 60% respectively both for the overall
 238 dataset and individual regions) with individual years treated as independent observations. Two
 239 random forest models were created, one using all the input variables and the other using only the
 240 TTOP model parameters (Table 3). The target variable for each random forest model was mean
 241 annual ground temperature at TTOP (MAGT). The random forests were generated in R Studio
 242 and run using the default settings for the number of variables sampled for splitting at each node
 243 (4 and 2 for iterations 1 and 2 respectively) and number of trees (500). For each iteration, the
 244 same training and test dataset was used to ensure comparability. The Northern NWT & NU
 245 ~~region was~~ regions were not included in this analysis as it had only one site with
 246 measured because they lacked sufficient deeper ground temperature at depth measurements.

247 **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

248
 249 Random forest provides variable importance rankings through two methods: permutation
 250 accuracy importance (mean square error (MSE) reduction) or Gini importance (Strobl et al.,
 251 2008). The former, used here, has been more widely employed in variable importance studies
 252 due to biases in Gini importance when predictor parameters vary in number and scale (Díaz-

253 Uriarte & Alvarez de Andrés, 2006; Strobl et al., 2008; Grömping, 2009; Genuer et al., 2010).
254 Reduction in MSE involves the random permutation of each variable individually to simulate its
255 absence in the model prediction. Variable importance is then determined based on the difference
256 in prediction accuracy before and after the permutation. Variable importance plots were created
257 for each random forest model both for the entire dataset (averaged across all sites) and for each
258 region individually: (averaged for all sites within each region) (e.g. Colyn et al. 2025).

259 **2.5 TTOP model performance**

260 For sites with measured ground temperature, the performance of the TTOP model was
261 assessed by comparing the calculated TTOP and the measured AMGT at or near the top of
262 permafrost (observed TTOP). For the few sites where the observed AMGT was not near the top
263 of the frost table, the observed AMGT was still compared to TTOP as the thermal offset at these
264 sites was low (S1). TTOP model performance was based on model root mean square error
265 (RMSE), r^2 , and bias compared to measured temperatures for individual years and sites.

266 **3 Results**

267 **3.1 TTOP Sensitivity**

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

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

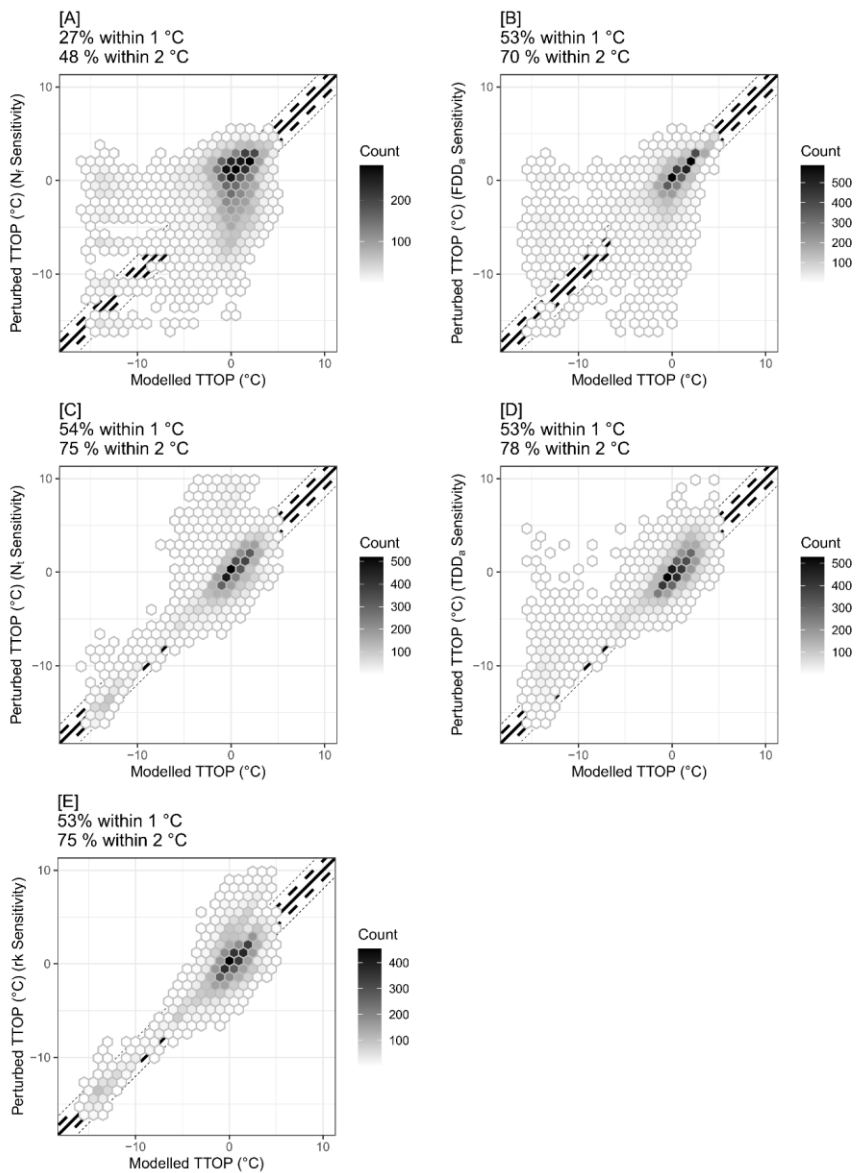
	<u>Mean ± Standard Deviation</u>	Minimum	10 th Percentile	25 th Percentile	50 th Percentile	75 th Percentile	90 th Percentile	Maximum
n_r	<u>0.34 ± 0.25</u>	0	0.06	0.15	0.29	0.48	0.76	1.0
n_t	<u>0.83 ± 0.32</u>	0.01	0.54	0.66	0.79	0.93	1.14	4.3
rk	<u>0.81 ± 0.26</u>	0.18	0.51	0.68	0.83	0.97	1.11	1.98
FDD_a (°C days)	<u>3051 ± 1132</u>	274	1851	2324	2857	3467	4588	7223
TDD_a (°C days)	<u>1378 ± 497</u>	150	727	1081	1438	1378	1944	2368

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277 For a majority (>53 %) of sample points, changes to FDD_a, n_t, TDD_a, and rk resulted in <
 278 1 °C difference between the reference and perturbed TTOP output (Fig. 2b,c,d,e). However, for
 279 n_r less than half (< 27 %) remained within 1 °C of the initial TTOP value (Fig. 2a). FDD_a showed
 280 more sensitivity than TDD_a, n_t, and rk with less than 70% of sample points remaining within 2
 281 °C of the initial observation value (compared to > 75 %).



282
 283 **Figure 2.** Reference TTOP model values compared to perturbed TTOP model values for the
 284 direct substitution of the minimum, 5th, 25th, 50th, 75th, 95th, and maximum percentile value for
 285 [A] n_f, [B] FDD_a, [C] n_t, [D] TDD_a, and [E] rk. Large dashes indicate a ± 1 °C difference while
 286 small dashes indicated a ± 2 °C difference.

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

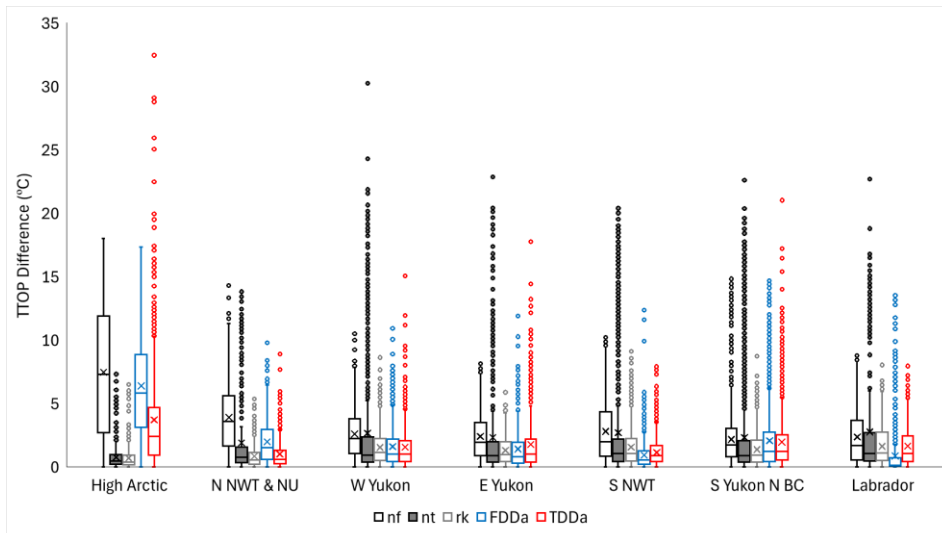
297 **Table 5.** Average absolute difference between the reference TTOP and the perturbed TTOP for
 298 each parameter within each region. Regions are High Arctic, Northern NWT & NU, Western
 299 Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern BC, and Labrador. Values
 300 followed by the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

303 ^a in column 2 indicates that the difference in TTOP for n_t and rk is not significantly different in
 304 the High Arctic.

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

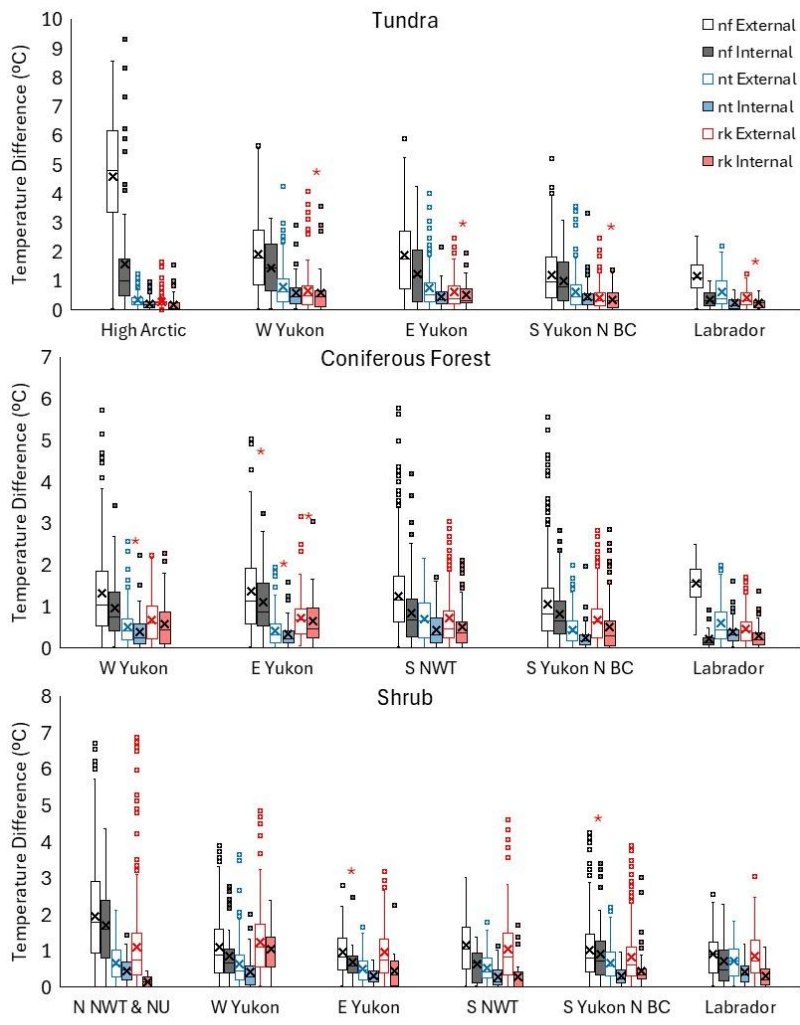
307



308
 309 **Figure 3.** Boxplots for the regional absolute difference between the reference TTOP and TTOP
 310 calculated when parameters were directly substituted to a percentile value. Mean values are
 311 represented by an X, outliers are shown as circles, and the ends of the whiskers show the value
 312 for one and a half times the interquartile range. The ends of the box show the first (25 percent)
 313 and third (75 percent) quartiles and the black line within the box shows the median.

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

319



320
 321 **Figure 4.** Boxplots for the difference between the measured ground temperature and the TTOP
 322 model using the internal parameter value (median value for the landcover type within the region)
 323 and the external parameter value (median value for the landcover type outside the region). Red
 324 asterisk (*) indicates the difference resulting from using the internal and external parameter
 325 value was not significant ($P > 0.05$). Mean values are represented by an X, outliers are shown as
 326 circles, and the ends of the whiskers show the value for one and a half times the interquartile
 327 range. The ends of the box show the first (25 percent) and third (75 percent) quartiles and the
 328 black line within the box shows the median.

329 **3.2 Random Forest**

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

336

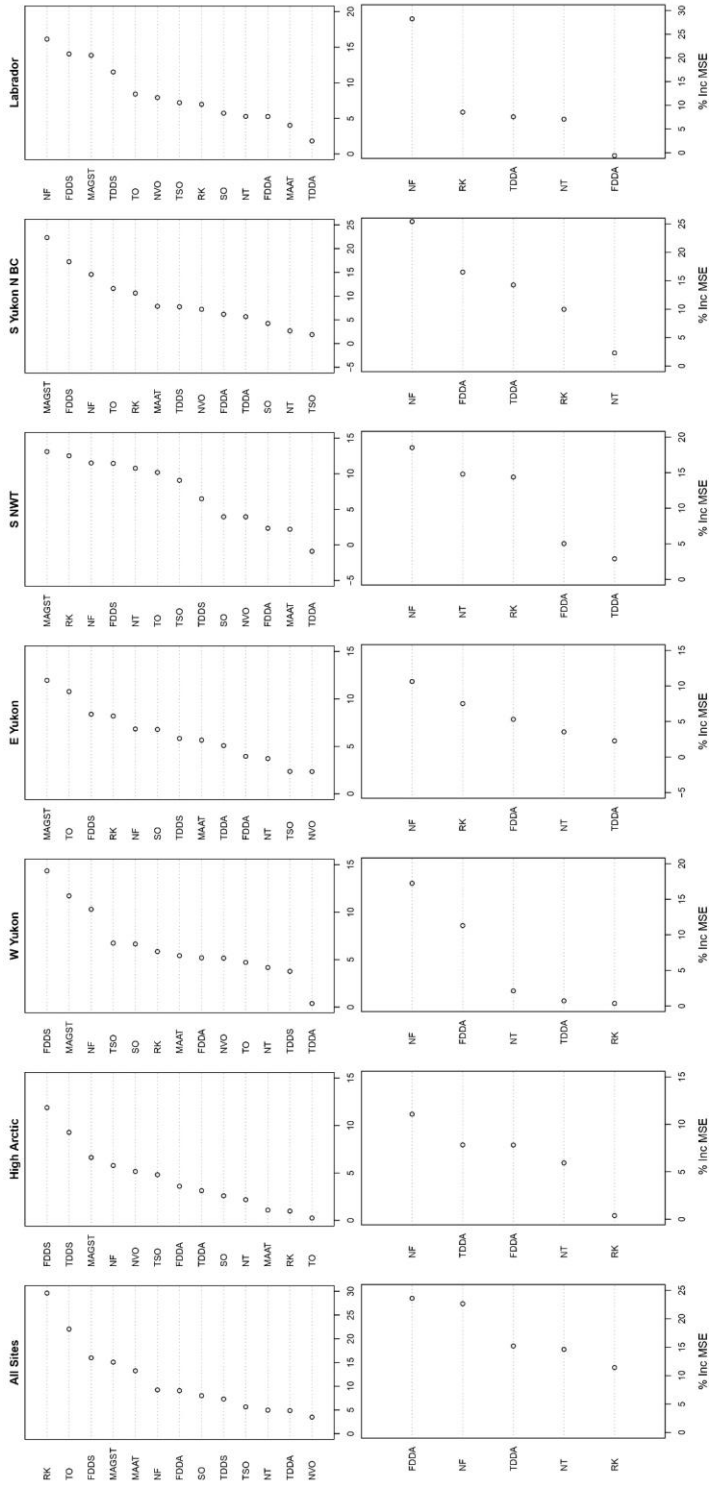


Figure 5. Variable importance plots for random forest models run using all variables (top row) or only parameters used in the standard form of the TTOP model (bottom row) for all sites and individual regions.

338
 339 When using only the TTOP model parameters, n_f was ranked as the most important for
 340 every region, while n_t , rk , and TDD_a most often ranked lower in importance. TDD_a was the
 341 second most important parameter for the High Arctic region but was not deemed to be of high
 342 importance for any other region. Overall, the variable importance rankings once again highlight
 343 the prominence of freezing season conditions compared to thawing.

344 3.3 Random Forest Variable Importance Rankings Compared to TTOP Sensitivity Results

345 The variable importance conclusions from the TTOP sensitivity and random forest using
 346 only the TTOP parameters did not match perfectly, but there were commonalities for certain
 347 parameters. When comparing parameter rankings between the TTOP sensitivity analysis and
 348 random forest all but n_f showed strong correlation (Table 6). Both analyses highlighted the
 349 importance of the freezing parameters (especially n_f). Three regions (High Arctic, Southern
 350 NWT, and Labrador) showed similarity) which had the highest (almost perfect) correlation.
 351 There were greater discrepancies in parameter importance between the two methods. The
 352 remaining regions showed greater discrepancies rankings, particularly in the rankings of for n_t and
 353 rk , which had the lowest correlations, especially n_t which was the only parameter to have a weak
 354 ranking correlation. Despite the methodological differences between the two analyses, both
 355 methods generally captured the parameter ranking showed good agreement, capturing the trends
 356 in the overall and regional differences in parameter importance.

357 Table 6. Spearman correlation between the parameter importance rankings for the TTOP
 358 sensitivity analysis and the random forest.

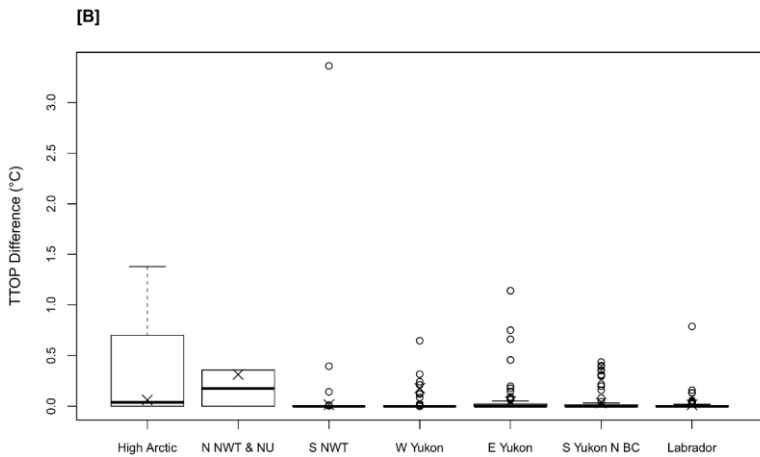
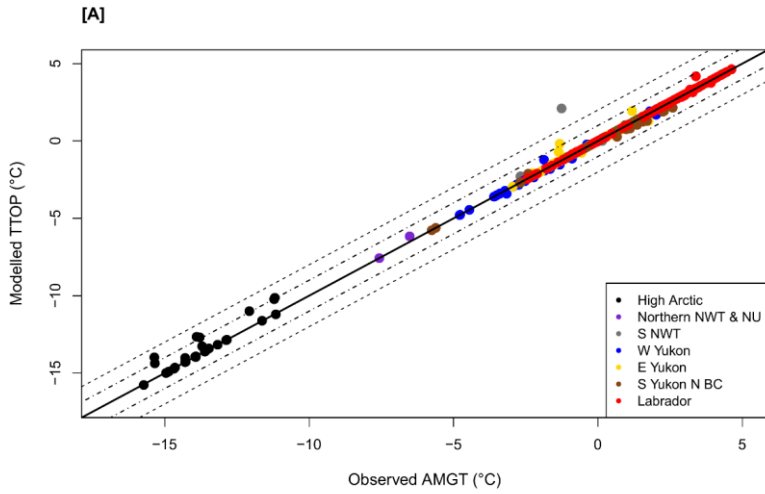
	<u>FDD_a</u>	<u>TDD_a</u>	<u>n_f</u>	<u>n_t</u>	<u>rk</u>
<u>Spearman Correlation</u>	<u>0.84</u>	<u>0.88</u>	<u>0.92</u>	<u>0.34</u>	<u>0.73</u>

359

360 3.4 TTOP Model Performance

361 The TTOP model performed well compared to the observed AMGT overall with an
362 RMSE of 0.2 °C, but with regional differences in model performance (Fig. 2-6). The model also
363 has a slight warm bias (0.02 °C) and a high r^2 (0.99). Model error was low in most regions,
364 except for the High Arctic. However, the Southern NWT ~~and Southern Yukon Northern BC~~
365 ~~regions~~region included ~~a number of outliers~~an outlier with ~~a large error~~error.

366



367
 368 **Figure 6. A)** Comparison of TTOP model outputs to the measured annual mean ground
 369 temperature (AMGT). The solid line in panel A is the 1:1 relation between modelled and
 370 observed while the dashed lines indicate 1 and 2 °C differences. **B)** Boxplots for the absolute
 371 difference between the modelled TTOP and the measured AMGT close to the frost table across
 372 the entire study area and for individual regions. Mean values are represented by an X, outliers are
 373 shown as circles, and the ends of the whiskers show the value for one and a half times the
 374 interquartile range. The ends of the box show the first (25 percent) and third (75 percent)
 375 quartiles and the black line within the box shows the median.

376 Additionally, the model only misclassified permafrost presence (TTOP < 0°C) or absence (TTOP
377 > 0 °C) at 3 of the 612 observations. Two of the three observations were in the Southern Yukon-
378 Northern BC region both of which were false positives for permafrost (no permafrost in
379 observation but negative modelled temperature). The third observation was in the SNWT region
380 where permafrost was observed but the model indicated its absence.

381 **4 Discussion**

382 **4.1 TTOP Model Parameter Sensitivity**

383 The sensitivity of the TTOP model to changes in specific parameters is affected by the
384 structure of the model and the values of the parameters. The model across all regions was most
385 sensitive to changes in n_f , due to the higher number of FDD_a (compared to TDD_a), which
386 amplified the response to changes (Smith & Riseborough, 1996, 2002; Bevington & Lewkowitz,
387 2015). Additionally, n_f represents the impact of freezing season air temperature and snow depth
388 which has an important influence on the ground thermal regime and therefore permafrost
389 occurrence in the discontinuous zone (Riseborough & Smith, 1998; Smith & Riseborough, 2002,
390 Gisnås et al., 2014; Way & Lapalme, 2021, Tutton et al., 2021; von Oppen et al., 2022).
391 Therefore, it is unsurprising that it was consistently ranked as an important parameter.

392 Regionally, the sensitivity of the model to changes in the thawing parameters, especially TDD_a
393 and n_t increased southward as the difference between FDD_a and TDD_a decreased. The exception
394 to this was the High Arctic, where the model was disproportionately sensitive to changes in
395 TDD_a despite the large contrast in the number of FDD_a and TDD_a in this region (up to five times
396 as many FDD_a as TDD_a). The increased sensitivity to changes in TDD_a likely results from the
397 high values of n_t and r_k , with values regularly approaching or exceeding 1.0. As a result, changes
398 in TDD_a were amplified in this region. This also potentially highlights the

399 ~~vulnerability~~sensitivity of this region to changes in ~~summer~~ climate ~~due to~~as the lack of ~~tall~~
400 vegetation ~~increasing~~reduces the ~~importance and influence~~potential buffering effect of
401 ~~MAAT~~warmer temperatures on the ground thermal regime compared to other regions with more
402 well-developed surface cover (Shur & Jorgenson, 2007; Throop et al., 2012; Smith et al., 2022).

403 It is also important to note this study perturbed TTOP model parameters using the entire
404 measured dataset. Therefore, sensitivity to certain parameters may be higher than for studies with
405 altered parameters based on values measured within a region which may have limited variability
406 (Way & Lewkowicz, 2018). As a result, our results may highlight relatively higher sensitivity for
407 different parameters such as n_t compared to n_f in Labrador (Way & Lewkowicz, 2018). However,
408 the sensitivity and random forest analysis results also agreed with variable importance rankings
409 overall across northern Canada, especially regarding the importance of n_f (Bevington &
410 Lewkowicz, 2015; Colyn et al., 2025).

411 The sensitivity analysis also showed that TTOP model parameters are not necessarily
412 transferable between regions with the same landcover class. This is especially true for n_f and n_t as
413 using the median values for the same landcover class, ~~but an external~~ from a different region
414 resulted in a significantly greater error than ~~utilized~~using the median value corresponding to the
415 ~~site's actual~~ region. This could be a result of the large range of environments sampled in this
416 analysis as previous studies have shown transferability of n_t between rock and forest landcovers
417 of Labrador and Southern Yukon (Way & Lewkowicz, 2018). However, utilizing n_f from
418 Southern Yukon in Labrador increased TTOP model errors (Way & Lewkowicz, 2016), which
419 supports our findings. The lack of transferability of n_f likely stems from differences in snow
420 depth and density across Canada (Bormann et al., 2013; Way & Lewkowicz, 2016, Simpson et
421 al., 2022). As a result, utilizing snow redistribution algorithms are likely a more viable way to

422 accurately capture),permafrost presence and temperature on national and circumpolar scales
423 (Gisnås et al., 2014; L'Hérault et al., 2017; Obu et al., 2019). However, using landcover as a
424 proxy even when parameter values were outside of the region still resulted in a smaller error
425 range than when values from the entire dataset (regardless of landcover type) were used.

426 Rk appears to be generally more transferable, especially for the limited number of tundra
427 sites which might be the result of restricted soil (and organic) development and moisture in this
428 landcover (Throop et al., 2012). Additionally, rk may have a smaller influence on ground
429 temperature in certain environments (Karjalainen et al., 2019) and therefore the importance (or
430 lack of transferability) may be masked by the large dataset. These results demonstrate the need
431 for caution in assuming the regional transferability of parameters, especially in environments
432 where values may differ substantially.

433 **4.2 Random Forest Variable Importance Rankings**

434 The variable importance rankings for the overall and regional datasets were a product of
435 differences in values of the measured field inputs. TO and rk were ranked as the most important
436 parameters when all variables were used. TO has previously been suggested as the most
437 important parameter for determining the southern extent of permafrost, under equilibrium
438 conditions, as a high TO can protect permafrost from higher air temperatures (Smith &
439 Riseborough, 2002). However, neither were ranked as the most important parameters in any of
440 the regional analyses. TO and rk had lower correlation with the other parameters, (0.06 – 0.49),
441 which may have artificially elevated their importance, but they are highly correlated with each
442 other (0.93) which may explain why both have elevated importance- (Fig. S4).

443 NVO has also been highlighted in the literature as an important parameter, determining
444 the northern and southern limit of discontinuous permafrost and influencing permafrost existence

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

455 **4.3 TTOP model performance**

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

464 The TTOP model did not perform as well in the High Arctic for certain observations,
465 especially those from Cape Bounty during 2016-2017, when the predicted TTOP was higher than
466 the observed values. The AMGST for 2016-2017 was substantially higher than those from the
467 previous years. Although the AMAT showed only a slight deviation, n_f at these sites decreased

468 substantially, indicating greater snow depths. As a result, the TTOP model parameters were not
469 in equilibrium with ground temperature for this year, yielding a larger discrepancy. Additionally,
470 one year at one site in the Southern NWT region was also an outlier. At this site the relatively
471 warm ground conditions during the freezing season led to a low nf (0.1) during this year
472 compared to the other 12 years (0.46 on average). However, despite the warm winter conditions
473 the annual mean ground temperature remained comparable to the other years, only increasing
474 slightly. As a result, the TTOP model produced a larger error for this site during this year but
475 produced low error at this location for the remaining years.

476 The TTOP model using measured parameters performed surprisingly well in locations of
477 warmer, more marginal permafrost or locations with seasonal frost, despite these locations
478 potentially being in disequilibrium with the current climate. However, these regions, especially
479 the Southern NWT also showed slightly increased error and Southern Yukon-Northern BC, also
480 included individual sites with the largest errors more outliers (Fig. 6a) showing & b) reflecting a
481 lack of consistency in model performance. These results may indicate sites with more ecosystem-
482 protected permafrost and high apparent TOs or disequilibrium conditions (Shur & Jorgenson,
483 2007; James et al., 2013; Vegter et al., 2024). It should be noted that even small temperature
484 errors can result in the misclassification of permafrost presence where ground temperatures are
485 close to 0 °C (Daly et al., 2022; Vegter et al., 2024) whereas the classification would be
486 unaffected even with a larger temperature error in the High Arctic. However, the model
487 accurately predicted permafrost presence or absence for the vast majority of observations (> 98
488 %) in this study even though 38% of observations were within -1 °C to +1 °C.

489 **4.4 Sources of Uncertainty**

490 The methods used to rank the importance of variables have their own uncertainties that
491 could affect the reliability of the results. First, since the percentiles were derived from the
492 observed data the range of values for each parameter differed and would vary if a different
493 dataset was used. Second, although random forest is able to cope with highly correlated variables
494 for prediction (Boulesteix et al., 2012), there are conflicting conclusions on the reliability of
495 variable importance rankings (Strobl & Zeileis, 2008; Nicodemos et al., 2010; Tolosi &
496 Lengauer, 2011; Gregorutti et al., 2017). For this study, a majority of the input parameters are
497 highly correlated with at least one other parameter as some parameters are used to derive others-
498 (Figures S4-6). This may have led the variable importance rankings of the random forest to be
499 unreliable when all parameters were used. Additionally, although the random forest model
500 using all variables performed relatively well (MSE 0.2 °C; variance explained 98%), the regional
501 models had lower percentages of variance explained (43 - 93 %) even though MSE was similar
502 (0.2 – 0.8 °C). This may have impacted the reliability of the variable importance rankings for
503 these models, as they may have accurately predicted ground temperature. Finally, it is important
504 to note that due to the nature of random forest, the variable importance rankings are not perfectly
505 repeatable. However, in several random forest runs the most important and least important
506 parameters were consistent even if they were not in the exact same order each time. Despite the
507 possible errors and uncertainty in the results of this, the variable importance analyses were in
508 general agreement for the two methods and supported findings from previous studies.

509 Variation in variable importance rankings between the two methods may also have
510 resulted from the difference in approaches. As the TTOP model utilized multiplicative factors,
511 the importance of the parameters was elevated by nature of the model equation. For example,
512 changes to FDD_a may be elevated through multiplication with n_r. The random forest variable

513 importance ranking was not dependent on this equation and as a result, the importance was
514 potentially different based on the predictive method alone. Additionally, the TTOP model
515 sensitivity analysis was determined through perturbation of the model parameters, thereby
516 ranking the parameters' importance based on the response. Contrastingly, the random forest
517 variable importance ranking was determined based on the current thermal conditions. This may
518 also have resulted in some discrepancy in the rankings. However, both methods showed similar
519 rankings and regional trends overall. Lastly, parameters sensitivity rankings do not inherently
520 relate to statistical importance. TTOP model sensitivity to changes in a parameter value may not
521 be statistically different from the sensitivity to changes in another (Table 5). This is especially
522 true for certain regions (N NWT & NU and the more southern regions), where there are few
523 statistically different sensitivities between parameters.

524 **4.5 Parameter classification recommendations**

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

534 Regionally, in locations where $FDD_a \gg TDD_a$, the impact of inadequate characterization
535 of n_f ~~and~~ r_k ~~and~~ was shown to be minimal. Therefore, more general assumptions and

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

548 Finally, many studies that determine TTOP characterize r_k using vegetation, assigning
549 values between 0.0 and 1.0 (Smith & Riseborough, 1996; Riseborough & Smith, 1998; Way &
550 Lewkowicz, 2016; Obu et al., 2019; Garibaldi et al., 2021). However, recent studies (including
551 the data analyzed for this study) have shown r_k values exceeding 1.0 (Bevington & Lewkowicz,
552 2015; Lin et al., 2015; Zou et al., 2017). This likely occurs as a product of extremely dry
553 conditions in winter and higher soil moisture during summer, resulting in greater thermal
554 conductivity in the warm season. This is typically observed at sites with rocky or bedrock
555 substrates and limited vegetation cover and soil moisture (Lin et al., 2015; Luo et al., 2018). In
556 southern permafrost environments, the assumption of $r_k < 1$ at these sites (such as high elevation
557 rocky slopes, Fig. 2b) likely results in mischaracterization of the permafrost condition. The
558 varying sensitivity of the TTOP model to specific parameters in different environments

559 demonstrates the need for accurate parameterization and validation of TTOP model parameters
560 to ensure valid outputs. This highlights the need for *in situ* ~~data~~-parameter data to increase the
561 accuracy of future TTOP modelling studies to validate remotely-derived parameter values.

562 **5 Conclusions**

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

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

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

587 **Data Availability**

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

590 **Author Contributions**

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

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

595 RGW – Conceptualization, Funding Acquisition, Investigation, Methodology, Writing (review
596 and editing)

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

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

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

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

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

603 HA – Data Curation, Writing (review and editing)

604 **Competing Interests**

605 The authors declare they have no competing interests

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621 **References**

- 622 Ackerman, H.: Spatial modelling of monthly climate across mountainous terrain in southern
623 Yukon and northern British Columbia, M.Sc. thesis, University of Ottawa, 2022
- 624 Aylsworth, J., & Kettles, I.: The Physical Environment of the Mackenzie Valley, Northwest
625 Territories: A Base Line for the Assessment of Environmental Change, Geological
626 Survey of Canada Bulletin 547, 49-55, 2000
- 627 Behnia, P., & Blais-Stevens, A.: Landslide susceptibility modelling using the quantitative
628 random forest method along the northern portion of the Yukon Alaska Highway Corridor,
629 Canada. *Natural hazards*, 90(3), 1407-1426, 2018
- 630 Bevington, A., & Lewkowicz, A. G.: Assessment of a land cover driven TTOP model for
631 mountain and lowland permafrost using field data, southern Yukon and northern British
632 Columbia, Canada, Proceedings of GéoQuebec: 68th Canadian Geotechnical Conference
633 and 7th Canadian Permafrost Conference, Quebec City, Canada, Paper 724
634 <https://members.cgs.ca/documents/conference2015/GeoQuebec/index.html>, 2015
- 635 Biau, G., & Scornet, E.: A random forest guided tour, *TEST*, 25(2), 197-227,
636 doi:10.1007/s11749-016-0481-7, 2016

637 Bonnaventure, P. P., Lewkowicz, A. G., Kremer, M., & Sawada, M. C.: A Permafrost
638 Probability Model for the Southern Yukon and Northern British Columbia, Canada,
639 Permafrost and Periglacial Processes, 23(1), 52-68, doi:10.1002/ppp.1733, 2012

640 Bormann, K. J., Westra, S., Evans, J. P., & McCabe, M. F.: [Spatial and temporal variability in](#)
641 [seasonal snow density. Journal of hydrology, 484, 63-73,](#)
642 <https://doi.org/10.1016/j.jhydrol.2013.01.032>, 2013

643 Boulesteix, A.-L., Janitza, S., Kruppa, J., & König, I. R.: Overview of random forest
644 methodology and practical guidance with emphasis on computational biology and
645 bioinformatics, WIREs Data Mining and Knowledge Discovery, 2(6), 493-507,
646 doi:<https://doi.org/10.1002/widm.1072>, 2012

647 Brieuc, M. S. O., Waters, C. D., Drinan, D. Naish, K. A.: [A practical introduction to Random](#)
648 [Forest for genetic association studies in ecology and evolution. Molecular Ecology](#)
649 [Resources., 18\(4\), 755-766, doi:https://doi.org/10.1111/1755-0998.12773](#), 2018

650 Burn, C., Moore, J., O'Neill, B., Hayley, D., Trimble, J., Calmels, F., . . . Idrees, M.: Permafrost
651 characterization of the Dempster Highway, Yukon and Northwest Territories.
652 Proceedings of GéoQuebec: 68th Canadian Geotechnical Conference and 7th Canadian
653 Permafrost Conference, Quebec City, Canada, Paper 705,
654 <https://members.cgs.ca/documents/conference2015/GeoQuebec/index.html>, 2015

655 Burn, C. R., & Kokelj, S. V.: The environment and permafrost of the Mackenzie Delta area.
656 Permafrost and Periglacial Processes, 20(2), 83-105, doi:10.1002/ppp.655, 2009

657 Brown, N. and Gruber, S.: Beyond MAGT: learning more from permafrost thermal monitoring
658 data with additional metrics, EGUSphere [preprint], [https://doi.org/10.5194/egusphere-](https://doi.org/10.5194/egusphere-2025-2658)
659 [2025-2658](https://doi.org/10.5194/egusphere-2025-2658), 2025.

660 Brown, J., Ferrians, O., Heginbottom, J. A. & Melnikov, E.: Circum-Arctic Map of Permafrost
661 and Ground-Ice Conditions. (GGD318, Version 2). [Data Set], Boulder, Colorado USA,
662 National Snow and Ice Data Center, <https://doi.org/10.7265/skbg-kf16>, 2002

663 Colyn, V., Way, R., Wang, Y., Beer, J., Trant, A., Hermanutz, L., ... & Le, N.: [Investigating](#)
664 [spatial variability of ground temperatures across coastal and continental highlands in](#)
665 [Labrador, northeastern Canada, Arctic Science, 11, 1-26, https://doi.org/10.1139/as-2024-](#)
666 [0079](https://doi.org/10.1139/as-2024-0079), 2025

667 Couture, N.J.: Sensitivity of permafrost terrain in a High Arctic polar desert: An evaluation of
668 response to disturbance near Eureka, Ellesmere Island, Nunavut. Montreal, Quebec,
669 Canada, Geography Department, McGill University, 2000.

670 Cutler, D. R., Edwards Jr., T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, & Lawler, J. J.:
671 [Random Forests for Classification in Ecology, Ecology, 88\(11\), 2783-2792,](#)
672 [doi:https://doi.org/10.1890/07-0539.1](https://doi.org/10.1890/07-0539.1), 2007

673 Daly, S. V., Bonnaventure, P. P., & Kochtitzky, W.: Influence of ecosystem and disturbance on
674 near-surface permafrost distribution, Whati, Northwest Territories, Canada, Permafrost
675 and Periglacial Processes, 33(4), 339-352, doi:10.1002/ppp.2160, 2022

676 Díaz-Uriarte, R., & Alvarez de Andrés, S.: Gene selection and classification of microarray data
677 using random forest, BMC Bioinformatics, 7(1), 3, doi:10.1186/1471-2105-7-3, 2006

678 Duchesne, C., Smith, S. L., Ednie, M., & Bonnaventure, P. P.: Active layer variability and
679 change in the Mackenzie Valley, Northwest Territories, Proc. 68th Canadian
680 Geotechnical Conf. and Seventh Canadian Conf. on Permafrost (GEOQuébec 2015),
681 Paper 67, <https://members.cgs.ca/documents/conference2015/GeoQuebec/index.html>,
682 2015

683 Environment Canada, Historical Data – Climate, Environment and Climate Change Canada
684 [dataset], https://climate.weather.gc.ca/historical_data/search_historic_data_e.html, 2017
685 Environment Canada, Historical Data – Climate, Environment and Climate Change Canada
686 [dataset], https://climate.weather.gc.ca/historical_data/search_historic_data_e.html, 2021
687 [Forget, A., Way, R., Wang, Y., Beer, J., Colyn, V., Tutton, R., Trant, A., Hermanutz, L.:](#)
688 [Evaluating local drivers of ground surface temperature variability in coastal Labrador.](#)
689 [Presented at the Proceedings of the 12th International Conference on Permafrost,](#)
690 [Canadian Permafrost Association, Whitehorse, Yukon, Canada, pp. 94–102.](#)
691 <https://doi.org/10.52381/ICOP2024.209.1.2024>
692 Garibaldi, M. C., Bonnaventure, P. P., & Lamoureux, S. F.: Utilizing the TTOP model to
693 understand spatial permafrost temperature variability in a High Arctic landscape, Cape
694 Bounty, Nunavut, Canada, *Permafrost and Periglacial Processes*, 32(1), 19-34,
695 <https://doi.org/10.1002/ppp.2086>, 2021
696 Garibaldi, M. C., Bonnaventure, P. P., Noad, N. C., & Kochtitzky, W.: Modelling air, ground
697 surface, and permafrost temperature variability across four dissimilar valleys, Yukon,
698 Canada, *Arctic Science*, 10(4), 611-629, <https://doi.org/10.1139/as-2023-0067>, 2024
699 Genuer, R., Poggi, J.-M., & Tuleau-Malot, C.: Variable selection using random forests, *Pattern*
700 *Recognition Letters*, 31(14), 2225-2236, doi:
701 <https://doi.org/10.1016/j.patrec.2010.03.014>, 2010
702 Gislås, K., Etzelmüller, B., Farbrot, H., Schuler, T. V., & Westermann, S.: CryoGRID 1.0:
703 Permafrost Distribution in Norway estimated by a Spatial Numerical Model, *Permafrost*
704 *and Periglacial Processes*, 24(1), 2-19, doi:10.1002/ppp.1765, 2013
705 [Gislås, K., Westermann, S., Schuler, T.V., Litherland, T., Isaksen, K., Boike, J., Etzelmüller, B.:](#)
706 [A statistical approach to represent small-scale variability of permafrost temperatures due](#)
707 [to snow cover. *The Cryosphere* 8, 2063–2074. <https://doi.org/10.5194/tc-8-2063-2014>,](#)
708 [2014](#)
709 Government of Canada, *Provinces/Territories, Cartographic Boundary File – 2016 Census*,
710 Statistics Canada [dataset]. [https://open.canada.ca/data/en/dataset/a883eb14-0c0e-45c4-](https://open.canada.ca/data/en/dataset/a883eb14-0c0e-45c4-b8c4-b54c4a819edb)
711 [b8c4-b54c4a819edb](https://open.canada.ca/data/en/dataset/a883eb14-0c0e-45c4-b8c4-b54c4a819edb), 2016
712 Government of Canada, *Lakes, Rivers, and Glaciers in Canada – CanVec Series – Hydrographic*
713 *Features*, Natural Resources Canada [dataset].
714 <https://open.canada.ca/data/en/dataset/9d96e8c9-22fe-4ad2-b5e8-94a6991b7446>, 2017
715 Gregorutti, B., Michel, B., & Saint-Pierre, P.: Correlation and variable importance in random
716 forests, *Statistics and Computing*, 27(3), 659-678, doi:10.1007/s11222-016-9646-1, 2017
717 Gregory F.M.: Biophysical Remote Sensing and Terrestrial CO₂ Exchange at Cape Bounty,
718 Melville Island, MSc thesis. Department of Geography, Queen's University, 2011
719 Grömping, U.: Variable Importance Assessment in Regression: Linear Regression versus
720 Random Forest, *The American Statistician*, 63(4), 308-319, doi:10.1198/tast.2009.08199,
721 2009
722 Guo, L., Ran, Y., Li, X., Jin, H. and Cheng, G.: Sensitivity of Permafrost Degradation to
723 Geological and Climatic Conditions, *Permafrost and Periglacial Processes*, 35, 450-460,
724 <https://doi.org/10.1002/ppp.2245>, 2024
725 Heginbottom, J. A., Dubreuil, M. A. & Harker, P. A.: Canada, permafrost: National Atlas of
726 Canada, MCR 4177 Canada Map Office, Contains information licensed under the Open
727 Government Licence – Canada, 1995

728 Henry, K., & Smith, M.: A model-based map of ground temperatures for the permafrost regions
729 of Canada, *Permafrost and Periglacial Processes*, 12(4), 389-398, doi:10.1002/ppp.399,
730 2001

731 Hodgson, D. A., Vincent, J.-S., & Fyles, J. G.: Quaternary geology of central Melville Island,
732 Northwest Territories; Geological Survey of Canada, Paper 83-16, 1984

733 Holloway, J.: Impacts of forest fire on permafrost in the discontinuous zones of northwestern
734 Canada, Doctoral dissertation, Université d'Ottawa/University of Ottawa, 2020

735 James, M., Lewkowicz, A. G., Smith, S. L., & Miceli, C. M.: Multi-decadal degradation and
736 persistence of permafrost in the Alaska Highway corridor, northwest Canada,
737 *Environmental Research Letters*, 8(4), 045013. DOI: 10.1088/1748-9326/8/4/045013,
738 2013

739 Juliussen, H., & Humlum, O.: Towards a TTOP ground temperature model for mountainous
740 terrain in central-eastern Norway, *Permafrost and Periglacial Processes*, 18(2), 161-184,
741 doi:10.1002/ppp.586, 2007

742 Karjalainen, O., Luoto, M., Aalto, J., & Hjort, J.: New insights into the environmental factors
743 controlling the ground thermal regime across the Northern Hemisphere: a comparison
744 between permafrost and non-permafrost areas, *The Cryosphere*, 13(2), 693-707,
745 doi:10.5194/tc-13-693-2019, 2019

746 Kersten, M. S.: Laboratory Research for the Determination of the Thermal Properties of Soils
747 (No. SIPRETR23), 1949

748 [L'Hérault, E., Boisson, A., Allard, M., Aubé-Maurice, S., Sarrazin, D., Roger, J., Barrette, C.:
749 Détermination et analyse des vulnérabilités du Nunavik en fonction des composantes
750 environnementales et des processus physique naturels liés au climat: Phase I, Rapport
751 produit pour le compte du Ministère des Forêts, de la Faune et des Parcs. Université
752 Laval, Québec City, Canada, 2017](#)

753 Lafrenière, M. J., & Lamoureux, S. F.: Effects of changing permafrost conditions on
754 hydrological processes and fluvial fluxes, *Earth-science reviews*, 191, 212-223,
755 <https://doi.org/10.1016/j.earscirev.2019.02.018>, 2019

756 Lewis, T., Lafrenière, M. J., & Lamoureux, S. F.: Hydrochemical and sedimentary responses of
757 paired High Arctic watersheds to unusual climate and permafrost disturbance, Cape
758 Bounty, Melville Island, Canada. *Hydrological Processes*, 26(13), 2003-2018,
759 doi:10.1002/hyp.8335, 2012

760 Lewkowicz, A. G., Bonnaventure, P. P., Smith, S. L., & Kuntz, Z.: Spatial and thermal
761 characteristics of mountain permafrost, northwest Canada, *Geografiska Annaler: Series
762 A, Physical Geography*, 94(2), 195-213, doi:10.1111/j.1468-0459.2012.00462.x, 2012

763 Lewkowicz, A.G.: Archiving University of Ottawa northern climate data, Report to Department
764 of Environment and Natural Resources, Government of the Northwest Territories, 2021

765 Li, R., Zhao, L., Wu, T., Wang, Q., Ding, Y., Yao, J., . . . Shi, J.: Soil thermal conductivity and
766 its influencing factors at the Tanggula permafrost region on the Qinghai-Tibet Plateau,
767 *Agricultural and Forest Meteorology*, 264, 235-246,
768 doi:<https://doi.org/10.1016/j.agrformet.2018.10.011>, 2019

769 Lin, Z., Burn, C. R., Niu, F., Luo, J., Liu, M., & Yin, G.: The Thermal Regime, including a
770 Reversed Thermal Offset, of Arid Permafrost Sites with Variations in Vegetation Cover
771 Density, Wudaoliang Basin, Qinghai-Tibet Plateau, *Permafrost and Periglacial Processes*,
772 26(2), 142-159, doi:<https://doi.org/10.1002/ppp.1840>, 2015

773 Luo, D., Jin, H., & Bense, V. F.: Ground surface temperature and the detection of permafrost in
774 the rugged topography on NE Qinghai-Tibet Plateau, *Geoderma*, 333, 57-68,
775 doi:<https://doi.org/10.1016/j.geoderma.2018.07.011>, 2019

776 Luo, D., Jin, H., Wu, Q., Bense, V. F., He, R., Ma, Q., . . . Lü, L.: Thermal regime of warm-dry
777 permafrost in relation to ground surface temperature in the Source Areas of the Yangtze
778 and Yellow rivers on the Qinghai-Tibet Plateau, SW China, *Science of The Total
779 Environment*, 618, 1033-1045, doi:<https://doi.org/10.1016/j.scitotenv.2017.09.083>, 2018

780 Medeiros, A.S., Friel, C.E., Finkelstein, S.A., Quinlan, R.: A high resolution multi-proxy record
781 of pronounced recent environmental change at Baker Lake, Nunavut, *J Paleolimnol*, 47,
782 661–676, <https://doi.org/10.1007/s10933-012-9589-2>, 2012

783 Meloche, J., Langlois, A., Rutter, N., McLennan, D., Royer, A., Billecocq, P., & Ponomarenko,
784 S.: High-resolution snow depth prediction using Random Forest algorithm with
785 topographic parameters: A case study in the Greiner watershed, Nunavut, *Hydrological
786 Processes*, 36(3), e14546, <https://doi.org/10.1002/hyp.14546>, 2022

787 Miner, K.R., Turetsky, M.R., Malina, E., Bartsch, A., Tamminen, J., McGuire, A.D., Fix, A.,
788 Sweeney, C., Elder, C.D., & Miller, C.E.: Permafrost carbon emissions in a changing
789 Arctic, *Nature Reviews Earth & Environment*, 3, 55-67, doi:10.1038/s43017-021-00230-
790 3, 2022

791 ~~Mitchell, J. B.: Machine learning methods in chemoinformatics, *Wiley Interdisciplinary
792 Reviews: Computational Molecular Science*, 4(5), 468-481, 2014~~

793 Nicholson, F.H., & Granberg, H.B: Permafrost and snow cover relationships near Schefferville,
794 In *Proceedings of the Second International Conference on Permafrost*, North American
795 Contribution, National Academy of Sciences, Washington, D.C., pp. 151-158, 1973

796 Nicodemus, K. K., Malley, J. D., Strobl, C., & Ziegler, A.: The behaviour of random forest
797 permutation-based variable importance measures under predictor correlation, *BMC
798 Bioinformatics*, 11(1), 110, doi:10.1186/1471-2105-11-110, 2010

799 Noad, N. C., & Bonnaventure, P. P.: Surface temperature inversion characteristics in dissimilar
800 valleys, Yukon Canada, *Arctic Science*, 2022;8(4); 1320-1339,
801 <https://doi.org/10.1139/as-2021-0048>, 2022

802 Noad, N. C., & Bonnaventure, P. P.: Examining the influence of microclimate conditions on the
803 breakup of surface-based temperature inversions in two proximal but dissimilar Yukon
804 valleys, *The Canadian Geographer/Le Géographe canadien*, 68(3), 303-431,
805 <https://doi.org/10.1111/cag.12886>, 2024

806 Obu, J., Westermann, S., Bartsch, A., Berdnikov, N., Christiansen, H. H., Dashtseren, A., . . .
807 Zou, D.: Northern Hemisphere permafrost map based on TTOP modelling for 2000–2016
808 at 1 km² scale, *Earth-Science Reviews*, 2019;193; 299-316.
809 doi:<https://doi.org/10.1016/j.earscirev.2019.04.023>, 2019

810 O'Neill, H. B., Smith, S. L., Burn, C. R., Duchesne, C., & Zhang, Y.: Widespread permafrost
811 degradation and thaw subsidence in northwest Canada, *Journal of Geophysical Research:
812 Earth Surface*, 128(8), e2023JF007262, <https://doi.org/10.1029/2023JF007262>, 2023

813 ~~Pastiek, N. J., Jorgenson, M. T., Wylie, B. K., Nield, S. J., Johnson, K. D., & Finley, A. O.:
814 Distribution of near-surface permafrost in Alaska: Estimates of present and future
815 conditions, *Remote Sensing of Environment*, 168, 301-315,
816 <https://doi.org/10.1016/j.rse.2015.07.019> 2015~~

817 [Pendergrass, D. C., Zhai, S., Kim, J., Koo, J. H., Lee, S., Bae, Riseborough, D. W.:](#) Exploring the
818 [parameters of a simple model of the permafrost-climate relationship \(Doctoral](#)
819 [dissertation, Carleton University\), 2004](#)

820 [M., ... Jacob, D. J.:](#) Continuous mapping of fine particulate matter (PM_{2.5}) air quality in East
821 [Asia at daily 6x6 km² resolution by application of a random forest algorithm to 2011–](#)
822 [2019 GOCI geostationary satellite data, *Atmos. Meas. Tech.*, 15\(4\), 1075–1091,](#)
823 [doi:10.5194/amt-15-1075-2022, 2022](#)

824 Riseborough, D.: The effect of transient conditions on an equilibrium permafrost-climate model,
825 *Permafrost and Periglacial Processes*, 18(1); 21-32. doi:10.1002/ppp.579, 2007

826 Riseborough, D., Shiklomanov, N., Etzelmüller, B., Gruber, S., & Marchenko, S.: Recent
827 advances in permafrost modelling, *Permafrost and Periglacial Processes*, 19(2); 137-156.
828 doi:10.1002/ppp.615, 2008

829 Riseborough, D., & Smith, M.: Exploring the limits of permafrost, Paper presented at the
830 Proceedings Permafrost: 7th International Conference, Yellowknife, Canada, Edited by
831 Lewkowicz, AG, and Allard, M. *Nordicana*, 54, 935-941, 1998

832 Roberts, K. E., Lamoureux, S. F., Kyser, T. K., Muir, D. C. G., Lafrenière, M. J., Iqaluk, D., ... &
833 Normandeau, A.: Climate and permafrost effects on the chemistry and ecosystems of
834 High Arctic Lakes. *Scientific Reports*, 7(1), 13292, [https://doi.org/10.1038/s41598-017-](https://doi.org/10.1038/s41598-017-13658-9)
835 [13658-9](https://doi.org/10.1038/s41598-017-13658-9), 2017

836 Romanovsky, V. E., Isaksen, K., Drozdov, D., Anisimov, O., Instanes, A., Leibman, M.,
837 McGuire, A. D., Shiklomanov, N., Smith, S., & Walker, D., Grosse, G., Jone, B. M.,
838 Jorgensen, M. T., Kanevskiy, M., Kizyakov, A., Lewkowicz, Chapter 4, A., Malkova, G.,
839 Marchenko, S., Niolsky, D. J., Sterletskiy, D., & Westermann, S.: Changing permafrost
840 and its impacts. In *Snow, Water, Ice and Permafrost in the Arctic (SWIPA) 2017. Arctic*
841 *Monitoring and Assessment Programme (AMAP)*, Oslo, Norway. 65–102.
842 ISBN 978-82-7971-101-8, 2017 [https://www.amap.no/documents/doc/snow-water-ice-](https://www.amap.no/documents/doc/snow-water-ice-and-permafrost-in-the-arctic-swipa-2017/1610)
843 [and-permafrost-in-the-arctic-swipa-2017/1610](https://www.amap.no/documents/doc/snow-water-ice-and-permafrost-in-the-arctic-swipa-2017/1610)

844 Shur, Y. L., & Jorgenson, M. T.: Patterns of permafrost formation and degradation in relation to
845 climate and ecosystems, *Permafrost and Periglacial Processes*, 18(1), 7-19,
846 doi:10.1002/ppp.582, 2007

847 [Simpson, I. R., Lawrence, D. M., Swenson, S. C., Hannay, C., McKinnon, K. A., & Truesdale, J.](#)
848 [E.:](#) Improvements in wintertime surface temperature variability in the Community Earth
849 [System Model version 2 \(CESM2\) related to the representation of snow density, *Journal*](#)
850 [of Advances in Modeling Earth Systems, 14\(4\), <https://doi.org/10.1029/2021MS002880>,](#)
851 [2022](https://doi.org/10.1029/2021MS002880)

852 Smith, M. W., & Riseborough, D. W.: Permafrost monitoring and detection of climate change,
853 *Permafrost and Periglacial Processes*, 7(4), 301-309, doi:10.1002/(sici)1099-
854 1530(199610)7:4<301::aid-ppp231>3.0.co;2-r, 1996

855 Smith, M. W., & Riseborough, D. W.: Climate and the limits of permafrost: a zonal analysis,
856 *Permafrost and Periglacial Processes*, 13(1), 1-15, doi:10.1002/ppp.410, 2002

857 Smith, S. L., O'Neill, H. B., Isaksen, K., Noetzli, J., & Romanovsky, V. E.: The changing
858 thermal state of permafrost. *Nature Reviews Earth & Environment*, 3(1), 10-23,
859 <https://doi.org/10.1038/s43017-021-00240-1>, 2022

860 Smith, S. L., Wolfe, S. A., Riseborough, D. W., & Nixon, F. M.: Active-layer characteristics and
861 summer climatic indices, Mackenzie Valley, Northwest Territories, Canada, *Permafrost*
862 *and Periglacial Processes*, 20(2), 201-220, doi:10.1002/ppp.651, 2009

863 Stanek, W., Alexander, K., & Simmons, C. S.: Reconnaissance of vegetation and soils along the
864 Dempster Highway, Yukon Territory: 1. Vegetation types, Report Pacific Forest
865 Research Centre (Canada), no. BC-X-217, 1980

866 Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T., & Zeileis, A.: Conditional variable
867 importance for random forests, *BMC Bioinformatics*, 9(1), 307, doi:10.1186/1471-2105-
868 9-307, 2008

869 Strobl, C., & Zeileis, A.: Danger: High power!—exploring the statistical properties of a test for
870 random forest variable importance, *COMPSTAT 2008 - Proceedings in Computational
871 Statistics*, Vol. II, 59 – 66, 2008.

872 Throop, J., Lewkowicz, A. G., & Smith, S. L.: Climate and ground temperature relations at sites
873 across the continuous and discontinuous permafrost zones, northern Canada, *Canadian
874 Journal of Earth Sciences*, 49(8), 865-876, <https://doi.org/10.1139/c11-075>, 2012

875 Tolosi, L., & Lengauer, T.: Classification with correlated features: unreliability of feature
876 ranking and solutions, *Bioinformatics*, 27(14), 1986-1994,
877 doi:10.1093/bioinformatics/btr300, 2011

878 [Tutton, R.J., Way, R.G., Beddoe, R., Zhang, Y., Trant, A.J.: Soil temperature sensitivity to
879 variable snow and vegetation conditions in low-relief coastal mountains, Nunatsiavut and
880 NunatuKavut, Labrador, in: Proceedings of the 2021 Regional Conference on Permafrost
881 & 19th International Conference on Cold Regions Engineering. American Society of
882 Civil Engineers, Boulder, Colorado, USA, pp. 71–81.
883 <https://doi.org/10.1061/9780784483589.007>, 2021](#)

884 Vegter, S., Bonnaventure, P. P., Daly, S., & Kochtitzky, W.: Modelling Permafrost Distribution
885 using the Temperature at Top of Permafrost Model in the Boreal Forest Environment of
886 Whatì, NT, *Arctic Science*, 10, 455-475, <https://doi.org/10.1139/as-2023-0010>, 2024

887 [von Oppen, J., Assman, J.J., Bjorkman, A.D., Treier, U.A., Elberling, B., Nabe-Nielsen, J.,
888 Normand, S.: Cross-scale regulation of seasonal microclimate by vegetation and snow in
889 the Arctic tundra. *Global Change Biology* 28, 7296–7312.
890 <https://doi.org/10.1111/gcb.16426>, 2022](#)

891 Walker, D. A., Gould, W. A., Maier, H. A., & Reynolds, M. K.: The Circumpolar Arctic
892 Vegetation Map: AVHRR-derived base maps, environmental controls, and integrated
893 mapping procedures, *International Journal of Remote Sensing*, 23(21), 4551-4570,
894 doi:10.1080/01431160110113854, 2002

895 [Way, R.G., Lapalme, C.M.: Does tall vegetation warm or cool the ground surface? Constraining
896 the ground thermal impacts of upright vegetation in northern environments. *Environ. Res.
897 Lett.* 16, 054077. <https://doi.org/10.1088/1748-9326/abef31>, 2021](#)

898 Way, R. G., & Lewkowicz, A. G.: Modelling the spatial distribution of permafrost in Labrador–
899 Ungava using the temperature at the top of permafrost, *Canadian Journal of Earth
900 Sciences*, 53(10), 1010-1028, doi:10.1139/cjes-2016-0034, 2016

901 Way, R. G., & Lewkowicz, A. G.: Environmental controls on ground temperature and permafrost
902 in Labrador, northeast Canada, *Permafrost and Periglacial Processes*, 29(2), 73-85,
903 doi:doi:10.1002/ppp.1972, 2018

904 [Yu, R., Yang, Y., Yang, L., Han, G., & Move, O. A.: RAQ—A Random Forest Approach for
905 Predicting Air Quality in Urban Sensing Systems, *Sensors*, 16\(1\), 86,
906 <https://doi.org/10.3390/s16010086>, 2016](#)

907 Zhang, T.: Influence of the seasonal snow cover on the ground thermal regime: An overview,
908 *Reviews of Geophysics*, 43(4), doi:10.1029/2004RG000157, 2005

909 Zou, D., Zhao, L., Sheng, Y., Chen, J., Hu, G., Wu, T., . . . Cheng, G.: A new map of permafrost
910 distribution on the Tibetan Plateau, *The Cryosphere*, 11(6), 2527-2542, doi:10.5194/tc-
911 11-2527-2017, 2017
912
913