

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

50 **1 Introduction**

51 Permafrost is an important element of the cryosphere, impacting, for example, terrain
52 stability (Romanovsky et al., 2017; Smith et al., 2022; O’Neill et al., 2023), carbon storage

53 (Miner et al., 2022), and solute movement (Roberts et al., 2017; Lafrenière & Lamoureux, 2019).
54 Unlike other elements of the cryosphere (e.g., glaciers and sea ice), direct observation of
55 permafrost is rare (Kääb, 2008) and modelling is often used to predict permafrost temperature
56 and distribution.

57 The Temperature at Top of Permafrost (TTOP) model (Riseborough & Smith, 1998) has
58 been used to estimate permafrost temperature and presence at continental to local scales (Henry
59 & Smith, 2001; Gislén et al., 2013; Way & Lewkowicz, 2016; Obu et al., 2019; Vegter et al.,
60 2024) and in a variety of permafrost environments including in the High Arctic and in mountains
61 (Bevington & Lewkowicz, 2015; Garibaldi et al., 2021; Garibaldi et al., 2024). Its extensive use
62 for spatial modelling is principally because it requires fewer input site condition and
63 meteorological variables than more complex one-dimensional numerical or surface energy
64 balance models. It has also been shown to be transferable to a variety of permafrost
65 environments without the need for extensive recalibration unlike empirical-statistical models
66 (Juliussen & Humlum, 2007; Riseborough et al., 2008). The primary challenge of using the
67 TTOP modelling approach is parameterization of the scaling factors (n-factors) and soil thermal
68 conductivities (Juliussen & Humlum, 2007). In modelling studies, these scaling factors have
69 typically been assigned based on landcover class or topographic class using field measurements
70 or values presented in the literature (Riseborough et al., 2008; Gislén et al., 2013; Obu et al.,
71 2019). Few studies have examined the uncertainties arising from mischaracterization of the
72 TTOP model parameter values or the relative importance of each parameter which may vary
73 substantially in different permafrost environments (Riseborough, 2004; Way & Lewkowicz,
74 2018).

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

88 TTOP parameters are also evaluated using a machine learning approach (random forest).
89 Random forest is a supervised machine learning technique which combines randomized decision
90 trees with bagging and aggregates their predictions through averaging or majority vote (Breiman
91 2001; Biau & Scornet, 2016). Random forest also allows determination of variable importance
92 rankings which can be used to either identify important variables for explanatory or interpolation
93 purposes or to identify a small number of variables that provide a good prediction (Díaz-Uriarte
94 & Alvarez de Andrés, 2006; Grömping, 2009; Genuer et al., 2010). In permafrost environments,
95 these importance rankings have been applied in analysis of snow depth and landslide potential
96 (Behnia & Blais-Stevens, 2018; Meloche et al., 2022) and have begun to be applied to analysis
97 of ground surface temperatures at a regional scale (Colyn et al., 2025). Continued adoption of

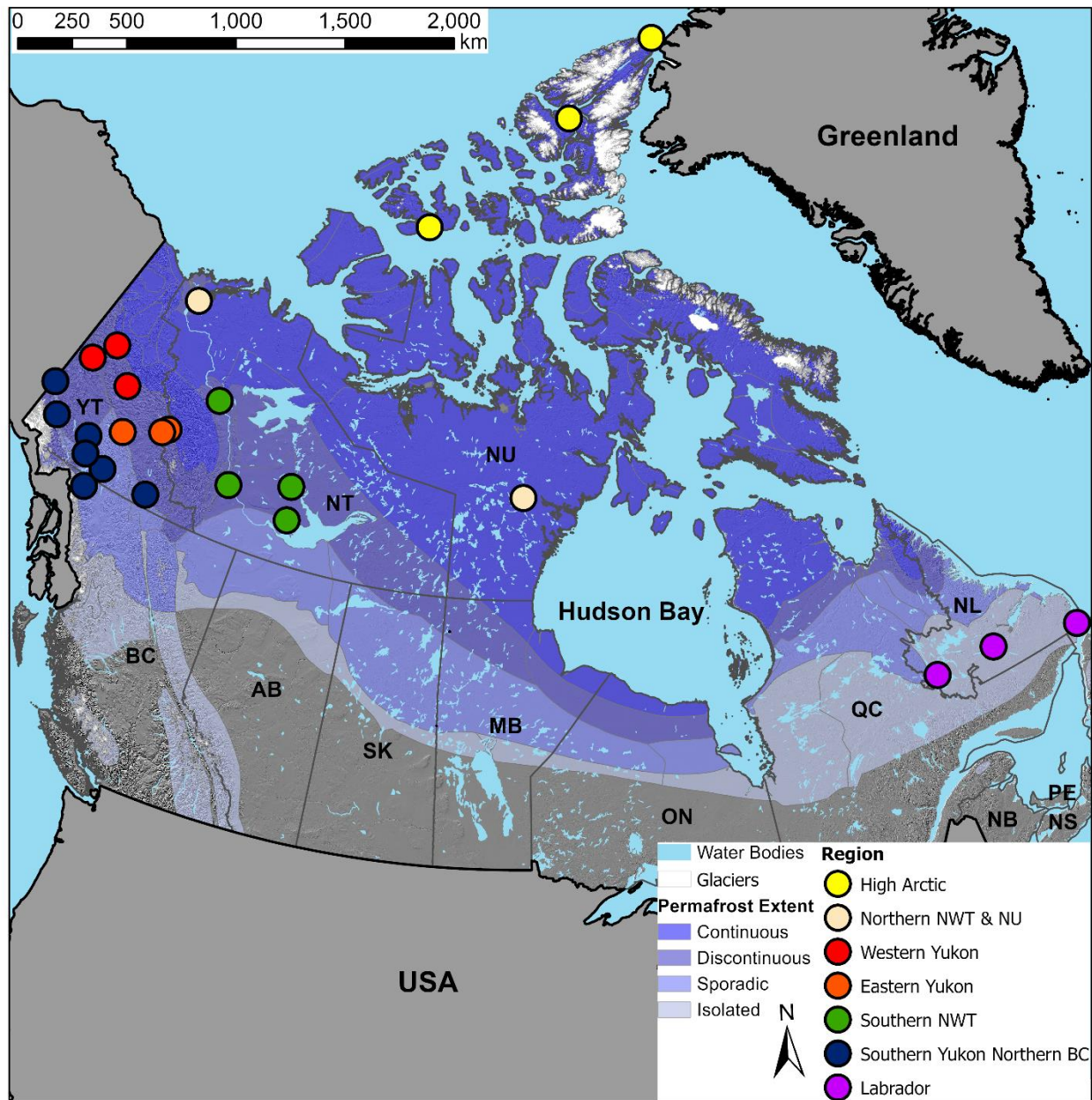
98 machine learning-based approaches to permafrost science and potential expansion of its use in
99 parameterizing process-based models highlights the need to improve our understanding of how
100 these models perform with real-world field data collected from across a variety of environments.

101 The objectives of this study are: (1) to use both a sensitivity analysis and machine
102 learning (random forest) to evaluate TTOP model parameter importance using field observations
103 and (2) to assess the accuracy of the TTOP model using measured parameters across permafrost
104 regions of Canada. These results will support future efforts to improve TTOP model parameter
105 calculations and to assess the performance of the TTOP model across differing environments.

106 **2 Methods**

107 **2.1 Study Area**

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



111
 112 **Figure 1.** Study area map showing the general location of the study sites used in the TTOP
 113 sensitivity analysis and random forest. The sites were grouped into seven regions for analysis
 114 (indicated by colour): High Arctic (Queen Elizabeth Islands), Northern NWT & NU, Western
 115 Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern British Columbia, and
 116 Labrador. Permafrost extent from Brown et al. (2002). Contains information licenced under the
 117 Open Government Licence – Canada.

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

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

123 **Table 1.** Environmental and sampling details for each study area including permafrost condition,
 124 mean annual air temperature (MAAT) for the 1991-2020 climate normal from closest EC station
 125 (if available), vegetation characteristics, number of sampling locations and length of monitoring
 126 period. Total number of observations is the number of individual years of data for each site in the
 127 region. (Stanek et al., 1980; Heginbottom et al., 1995; Aylsworth & Kettles, 2000; Smith et al.,
 128 2009b; Gregory, 2011; Medeiros et al., 2012; Bevington & Lewkowicz, 2015; Duchesne et al.,
 129 2015; Holloway, 2020; Daly et al., 2022; Environment and Climate Change Canada, 2021;
 130 Lewkowicz, 2021; Ackerman, 2022; Tutton et al., 2021; Garibaldi et al., 2024a; Garibaldi et al.,
 131 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
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
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	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
WhaTi	S NWT	-4.6	Patchwork of coniferous and mixed wooded forest, peat plateaus, and wetlands	Extensive Discontinuous	10	0	2019-2022	15
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
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
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
Mac Valley South	S NWT	-2.3	Boreal forest with extensive peatlands	Extensive Discontinuous	3	22	1993-2012	174
Mac Valley Central	S NWT	-5.5 to -4.8	Boreal Forest with extensive peatlands	Extensive Discontinuous	4	10	1993-2012	81

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133 2.2 Data Collection

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

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

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

149 For most sites, ground temperature at depth was measured using the Hobo U23-002 or
150 Hobo Pro U12-008 external thermistors, while for the remaining sites, ground temperatures at
151 depth were recorded using multi-sensor cables with RBR loggers. For a majority of sites, the
152 ground depth sensor was positioned close to or at the top of the frost table at the time of
153 installation. For sites with multiple ground temperature observations, the sensor closest to the
154 depth of the frost table was used. However, for less than a quarter of observations (23%), annual
155 mean ground temperature (AMGT) may not correspond to the temperature at the top of the frost
156 table due to installation depth limitations. These sites are generally confined to coarse grained,
157 dry, rocky sediment where the thermal gradient is typically small (Lewkowicz et al., 2012).
158 Based on estimations of active layer or frost depth and temperature extrapolation (S1), the
159 difference between the true TTOP and the temperature at the monitoring depth was generally less

160 than 0.5 °C (90 % observations, average = 0.2 °C). Therefore, at these sites, AMGT was still
161 compared directly to the modelled TTOP value.

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

167 **2.3 TTOP Model Sensitivity**

168 The TTOP model calculates equilibrium permafrost temperature using air freezing and
169 thawing degree days, n-factors and the thermal conductivity ratio (Table 2). The TTOP model is
170 often used spatially as the meteorological input parameters are commonly able to be estimated
171 from meteorological stations (Juliussen & Humlum, 2007). However, as an equilibrium model,
172 TTOP is not ideal for modelling transient changes in permafrost temperature and distribution.
173 TTOP model errors are often largest near 0°C due to latent heat effects, which the model does
174 not consider (Riseborough, 2007).

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

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

Variable	Abbreviation	Equation
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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	$FDD = \Sigma_1^P T , < 0$
Thawing Degree Days (°C days)	TDD	$TDD = \Sigma_1^P T , T > 0$
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	$TO = MAGT - MAGST$

182

183 To allow for direct comparison of model sensitivity in all environments with measured data, the
184 TTOP model equation for permafrost was also applied to sites considered to be seasonally frozen
185 (Way & Lewkowicz, 2018; Obu et al., 2019; Garibaldi et al., 2021). For each year and each site,
186 FDD and TDD were calculated using daily average air (T_a) and ground surface temperatures (T_s)
187 from September 1st to August 31st of the subsequent year. Freezing and thawing n-factors were
188 then calculated for each measurement location (Table 2). The ratio of thawed to frozen thermal
189 conductivity (rk) for sites with a deeper ground temperature measurement was calculated using
190 FDD and TDD for both the ground surface ($_s$) and the ground temperature observation at or near
191 the frost table ($_g$) (Table 2). For sites without a depth sensor, rk, was assigned based on
192 vegetation class for the High Arctic and substrate for the Mackenzie Valley ($n = 38$) (Kersten,
193 1949; Gregory, 2011; Obu et al., 2019; Garibaldi et al., 2021). These sites were included even
194 though rk needed to be assigned as they filled a substantial latitudinal gap in the dataset (Fig.

195 S2). Using the observed thermal offset to determine r_k may not necessarily be possible given the
196 materials that are present due to potential disequilibrium. However, for the purposes of this study
197 we assumed equilibrium conditions for each observation.

198 Once the parameters and reference TTOP values were determined, the sensitivity of the
199 model to changes in each parameter was assessed by iteratively substituting values for one
200 parameter while holding all other inputs constant and then calculating the TTOP value for each
201 substitution. The substituted values used percentiles (minimum, 10th, 25th, 50th, 75th, 90th and
202 maximum) calculated using the parameters across the entire study dataset. We selected
203 percentile-based substitution to test TTOP Model sensitivity as it allowed us to increase and
204 decrease parameter values within observed ranges while avoiding introducing negative values.
205 Additionally, percentile substitution allows for a direct comparison of sensitivity to each
206 parameter across regions as the parameters at all sites were changed to the same value. Each year
207 of data for each site was treated as its own observation and run through the sensitivity analysis
208 resulting in 9100 different TTOP values for each parameter. Sensitivity analysis TTOPs were
209 then compared to the reference (i.e observed) TTOP values to assess the influence of the TTOP
210 model to changes in each parameter.

211 Since vegetation is often used when assigning n -factors and r_k in regions without
212 observations, the TTOP sensitivity analysis was re-run using the median value for these
213 parameters based on vegetation class and region. These TTOP outputs were then compared to the
214 reference TTOP value for each site.

215 **2.4 Random Forest Variable Importance Ranking**

216 Algorithm inputs included TTOP model and additional parameters (see Table 2). Samples
 217 were randomly split into testing and training data (40% and 60% respectively both for the overall
 218 dataset and individual regions) with individual years treated as independent observations. Two
 219 random forest models were created, one using all the input variables and the other using only the
 220 TTOP model parameters (Table 3). The target variable for each random forest model was mean
 221 annual ground temperature at TTOP (MAGT). The random forests were generated in R Studio
 222 and run using the default settings for the number of variables sampled for splitting at each node
 223 (4 and 2 for iterations 1 and 2 respectively) and number of trees (500). For each iteration, the
 224 same training and test dataset was used to ensure comparability. The Northern NWT & NU
 225 regions were not included in this analysis because they lacked sufficient deeper ground
 226 temperature measurements.

227 **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

228

229 Random forest provides variable importance rankings through two methods: permutation
 230 accuracy importance (mean square error (MSE) reduction) or Gini importance (Strobl et al.,
 231 2008). The former, used here, has been more widely employed in variable importance studies
 232 due to biases in Gini importance when predictor parameters vary in number and scale (Díaz-
 233 Uriarte & Alvarez de Andrés, 2006; Strobl et al., 2008; Grömping, 2009; Genuer et al., 2010).
 234 Reduction in MSE involves the random permutation of each variable individually to simulate its

235 absence in the model prediction. Variable importance is then determined based on the difference
 236 in prediction accuracy before and after the permutation. Variable importance plots were created
 237 for each random forest model both for the entire dataset (averaged across all sites) and for each
 238 region individually (averaged for all sites within each region) (e.g. Colyn et al. 2025).

239 **2.5 TTOP model performance**

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

246 **3 Results**

247 **3.1 TTOP Sensitivity**

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

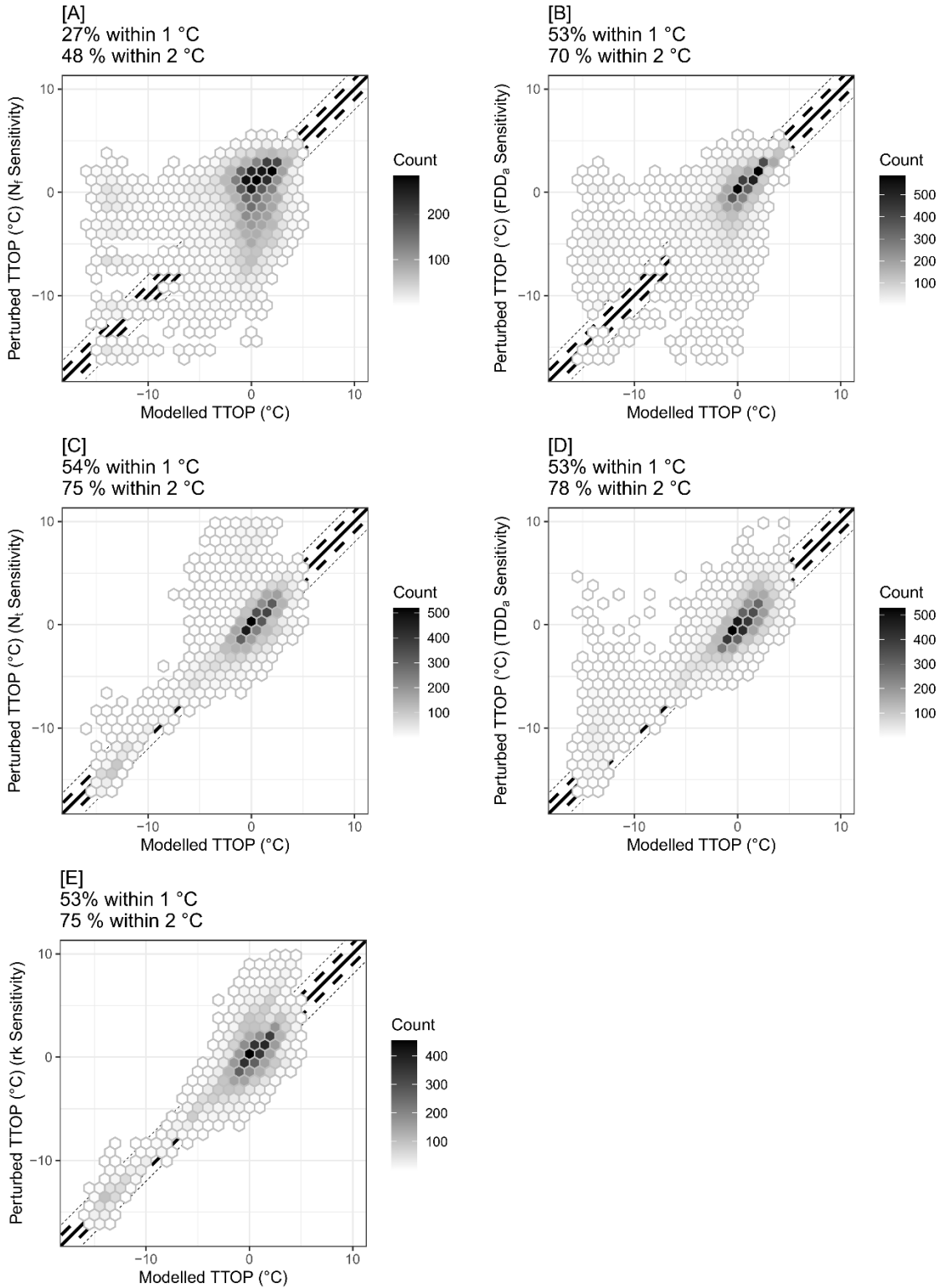
253 **Table 4.** Substituted percentile values for each parameter replacing the measured parameter
 254 value for each iteration of this trial method. These values were determined based on the
 255 observation data.

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

256

257 For a majority (>53 %) of sample points, changes to FDD_a, n_t, TDD_a, and rk resulted in <
258 1 °C difference between the reference and perturbed TTOP output (Fig. 2b,c,d,e). However, for
259 n_f less than half (< 27 %) remained within 1 °C of the initial TTOP value (Fig. 2a). FDD_a showed
260 more sensitivity than TDD_a, n_t, and rk with less than 70% of sample points remaining within 2
261 °C of the initial observation value (compared to > 75 %).



262
 263 **Figure 2.** Reference TTOP model values compared to perturbed TTOP model values for the
 264 direct substitution of the minimum, 5th, 25th, 50th, 75th, 95th, and maximum percentile value for
 265 [A] n_f, [B] FDD_a, [C] n_t, [D] TDD_a, and [E] rk. Large dashes indicate a ± 1 °C difference while
 266 small dashes indicated a ± 2 °C difference.

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

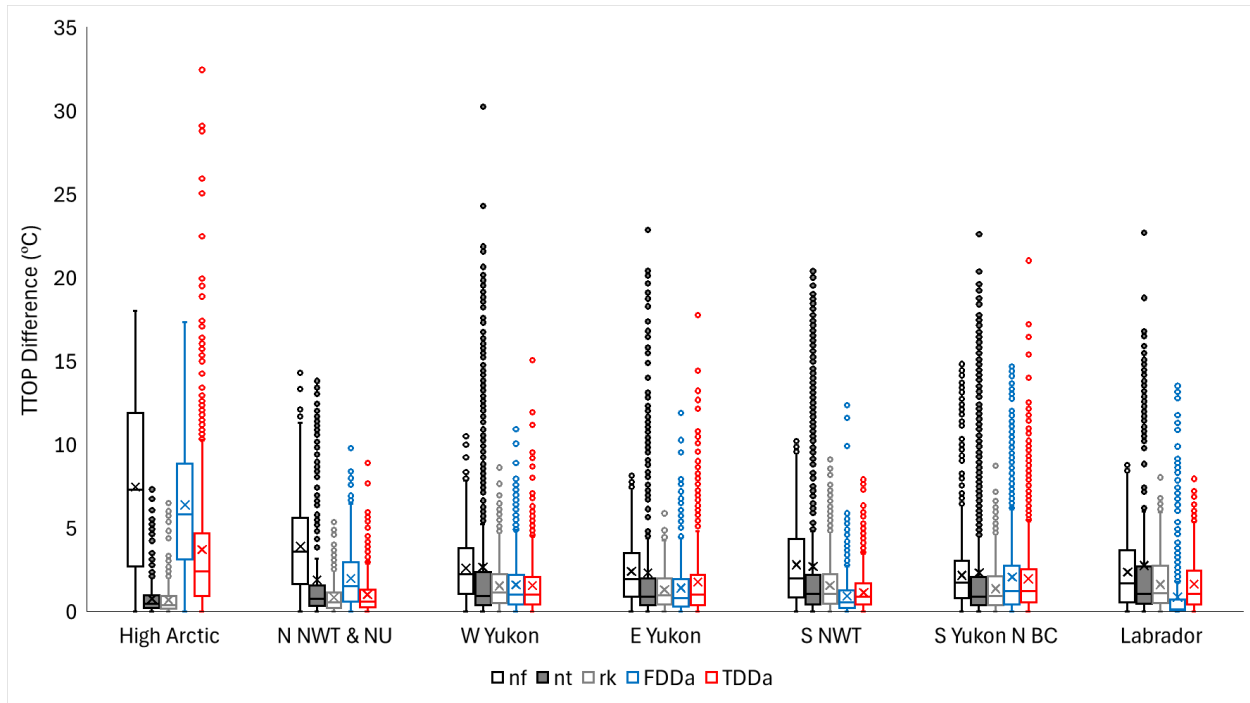
277 **Table 5.** Average absolute difference between the reference TTOP and the perturbed TTOP for
 278 each parameter within each region. Regions are High Arctic, Northern NWT & NU, Western
 279 Yukon, Eastern Yukon, Southern NWT, Southern Yukon-Northern BC, and Labrador. Values
 280 followed by the same superscript letter are not significantly different (P > 0.05) between regions
 281 (along a row). Values followed by a subscript italicized letter are not significantly different (P >
 282 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

283 _a in column 2 indicates that the difference in TTOP for n_t and rk is not significantly different in
 284 the High Arctic.

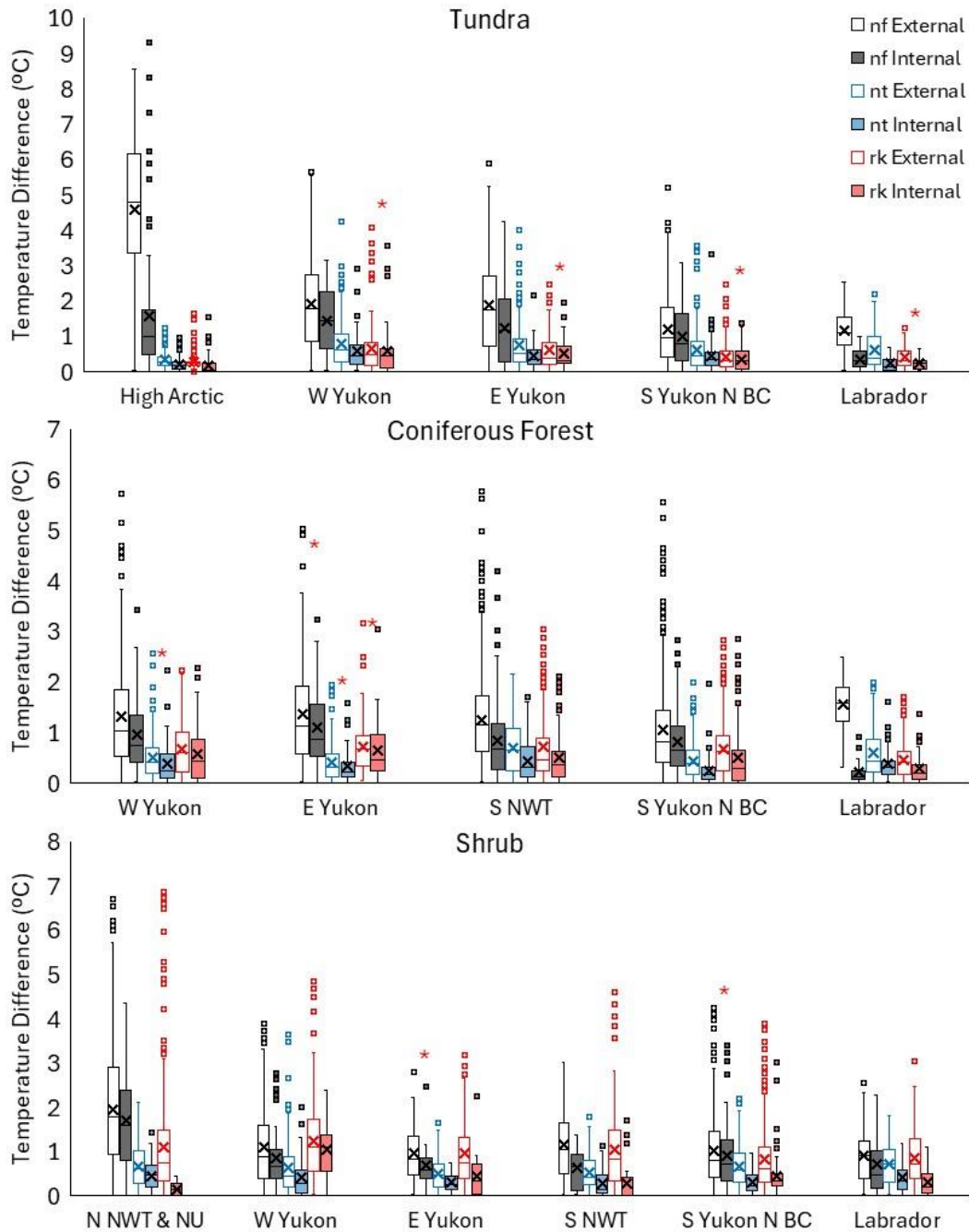
285 ^a in the second row indicates that the difference in TTOP for changes in FDD_a is not significantly
 286 different for the Northern NWT & NU and the Southern Yukon-Northern BC regions.

287



288 **Figure 3.** Boxplots for the regional absolute difference between the reference TTOP and TTOP
 289 calculated when parameters were directly substituted to a percentile value. Mean values are
 290 represented by an X, outliers are shown as circles, and the ends of the whiskers show the value
 291 for one and a half times the interquartile range. The ends of the box show the first (25 percent)
 292 and third (75 percent) quartiles and the black line within the box shows the median.
 293

294 Using the internal median parameter value (based on measured values for each landcover
 295 class within each region) resulted in a lower error than using the external median parameter
 296 value for every region and landcover class (Fig. 4). These differences were especially
 297 pronounced for n_f . For each region the shrub landcover class showed the least difference when
 298 using the internal vs. external parameters.
 299



300

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

309 3.2 Random Forest

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

316

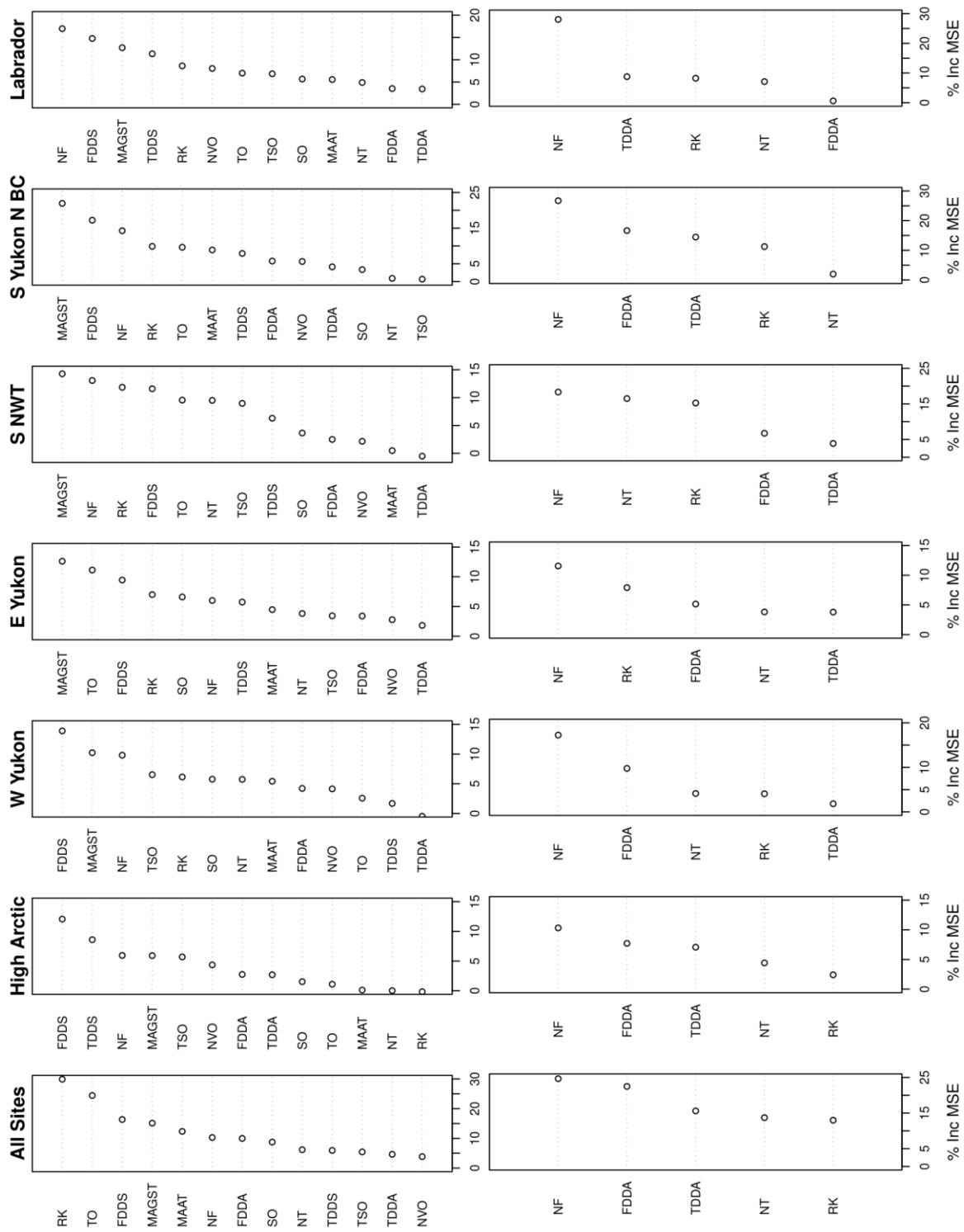


Figure 5. Variable importance plots for random forest models run using all variables (top row) or only parameters used in the standard form of the TTOP model (bottom row) for all sites and individual regions.

318

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

324 3.3 Random Forest Variable Importance Rankings Compared to TTOP Sensitivity Results

325 The variable importance conclusions from the TTOP sensitivity and random forest using
326 only the TTOP parameters did not match perfectly, but there were commonalities for certain
327 parameters. When comparing parameter rankings between the TTOP sensitivity analysis and
328 random forest all but n_t showed strong correlation (Table 6). Both analyses highlighted the
329 importance of the freezing parameters (especially n_f) which had the highest (almost perfect)
330 correlation. There were greater discrepancies in parameter importance rankings, particularly for
331 n_t and rk which had the lowest correlations, especially n_t which was the only parameter to have a
332 weak ranking correlation. Despite the methodological differences between the two analyses, the
333 parameter ranking showed good agreement, capturing the trends in the overall and regional
334 differences in parameter importance.

335 **Table 6.** Spearman correlation between the parameter importance rankings for the TTOP
336 sensitivity analysis and the random forest.

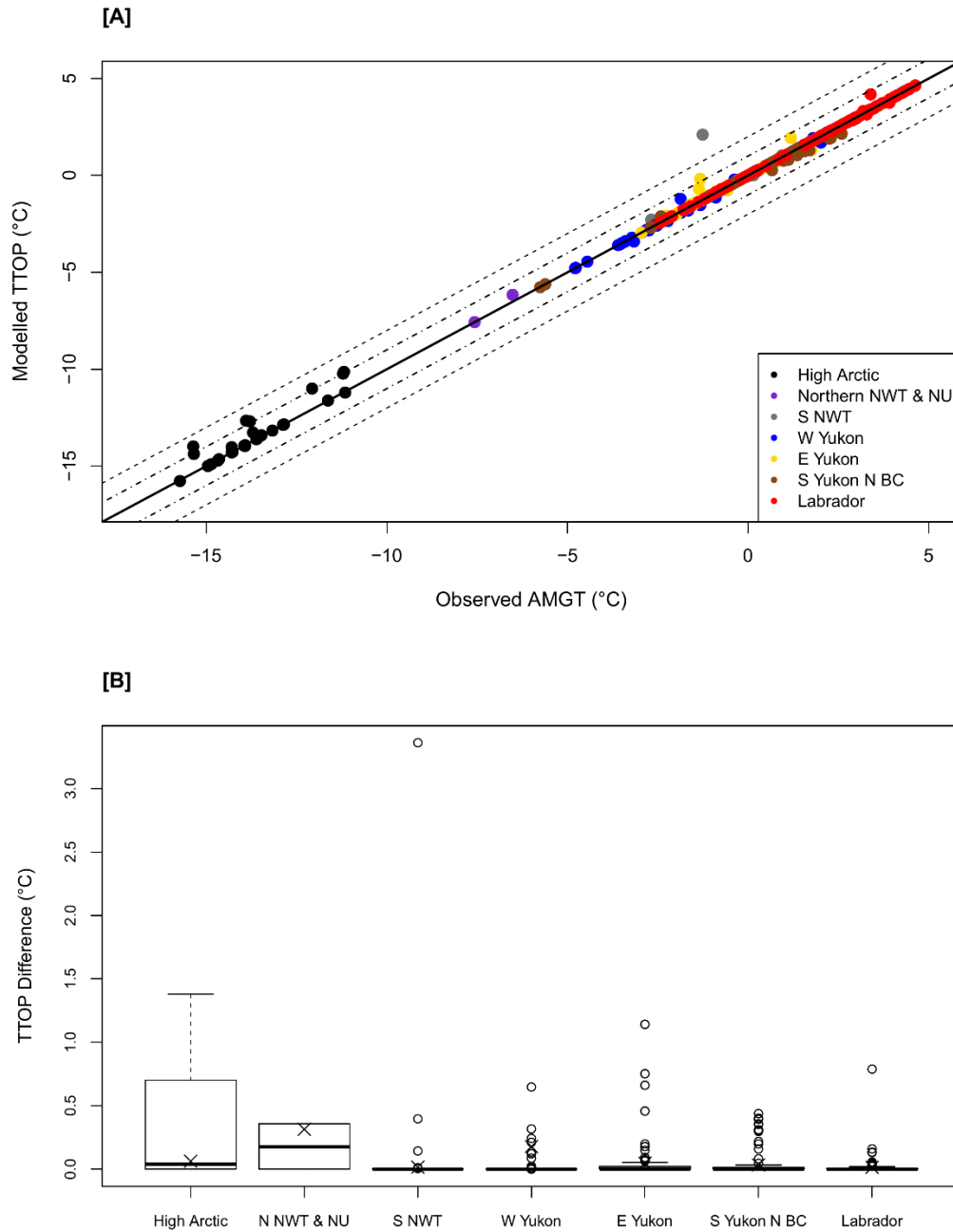
	FDD_a	TDD_a	n_f	n_t	rk
Spearman Correlation	0.84	0.88	0.92	0.34	0.73

337

338 3.4 TTOP Model Performance

339 The TTOP model performed well compared to the observed AMGT overall with an
340 RMSE of 0.2 °C, but with regional differences in model performance (Fig. 6). The model also
341 has a slight warm bias (0.02 °C) and a high r^2 (0.99). Model error was low in most regions,

342 except for the High Arctic. However, the Southern NWT region included an outlier with a large
343 error.



344
345 **Figure 6. A)** Comparison of TTOP model outputs to the measured annual mean ground
346 temperature (AMGT). The solid line in panel A is the 1:1 relation between modelled and
347 observed while the dashed lines indicate 1 and 2 °C differences. **B)** Boxplots for the absolute
348 difference between the modelled TTOP and the measured AMGT close to the frost table across
349 the entire study area and for individual regions. Mean values are represented by an X, outliers are
350 shown as circles, and the ends of the whiskers show the value for one and a half times the

351 interquartile range. The ends of the box show the first (25 percent) and third (75 percent)
352 quartiles and the black line within the box shows the median.

353 Additionally, the model only misclassified permafrost presence ($TTOP < 0^{\circ}\text{C}$) or absence ($TTOP$
354 $> 0^{\circ}\text{C}$) at 3 of the 612 observations. Two of the three observations were in the Southern Yukon-
355 Northern BC region both of which were false positives for permafrost (no permafrost in
356 observation but negative modelled temperature). The third observation was in the SNWT region
357 where permafrost was observed but the model indicated its absence.

358 **4 Discussion**

359 **4.1 TTOP Model Parameter Sensitivity**

360 The sensitivity of the TTOP model to changes in specific parameters is affected by the
361 structure of the model and the values of the parameters. The model across all regions was most
362 sensitive to changes in n_f , due to the higher number of FDD_a (compared to TDD_a), which
363 amplified the response to changes (Smith & Riseborough, 1996, 2002; Bevington & Lewkowicz,
364 2015). Additionally, n_f represents the impact of freezing season air temperature and snow depth
365 which has an important influence on the ground thermal regime and therefore permafrost
366 occurrence in the discontinuous zone (Riseborough & Smith, 1998; Smith & Riseborough, 2002,
367 Gislén et al., 2014; Way & Lapalme, 2021, Tutton et al., 2021; von Oppen et al., 2022).
368 Therefore, it is unsurprising that it was consistently ranked as an important parameter.
369 Regionally, the sensitivity of the model to changes in the thawing parameters, especially TDD_a
370 and n_t increased southward as the difference between FDD_a and TDD_a decreased. The exception
371 to this was the High Arctic, where the model was disproportionately sensitive to changes in
372 TDD_a despite the large contrast in the number of FDD_a and TDD_a in this region (up to five times
373 as many FDD_a as TDD_a). The increased sensitivity to changes in TDD_a likely results from the

374 high values of n_t and r_k , with values regularly approaching or exceeding 1.0. As a result, changes
375 in TDD_a were amplified in this region. This also potentially highlights the sensitivity of this
376 region to changes in summer climate as the lack of tall vegetation reduces the potential buffering
377 effect of warmer temperatures on the ground thermal regime compared to other regions with
378 more well-developed surface cover (Shur & Jorgenson, 2007; Throop et al., 2012; Smith et al.,
379 2022).

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

388 The sensitivity analysis also showed that TTOP model parameters are not necessarily
389 transferable between regions with the same landcover class. This is especially true for n_f and n_t as
390 using the median values for the same landcover class from a different region resulted in a
391 significantly greater error than using the median value corresponding to the site's actual region.
392 This could be a result of the large range of environments sampled in this analysis as previous
393 studies have shown transferability of n_t between rock and forest landcovers of Labrador and
394 Southern Yukon (Way & Lewkowicz, 2018). However, utilizing n_f from Southern Yukon in
395 Labrador increased TTOP model errors (Way & Lewkowicz, 2016), which supports our findings.
396 The lack of transferability of n_f likely stems from differences in snow depth and density across

397 Canada (Bormann et al., 2013; Way & Lewkowicz, 2016, Simpson et al., 2022). As a result,
398 utilizing snow redistribution algorithms are likely a more viable way to accurately capture
399).permafrost presence and temperature on national and circumpolar scales (Gisnås et al., 2014;
400 L'Hérault et al., 2017; Obu et al., 2019). However, using landcover as a proxy even when
401 parameter values were outside of the region still resulted in a smaller error range than when
402 values from the entire dataset (regardless of landcover type) were used.

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

410 **4.2 Random Forest Variable Importance Rankings**

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

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

432 **4.3 TTOP model performance**

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

441 The TTOP model did not perform as well in the High Arctic for certain observations,
442 especially those from Cape Bounty during 2016-2017, when the predicted TTOP was higher than

443 the observed values. The AMGST for 2016-2017 was substantially higher than those from the
444 previous years. Although the AMAT showed only a slight deviation, n_f at these sites decreased
445 substantially, indicating greater snow depths. As a result, the TTOP model parameters were not
446 in equilibrium with ground temperature for this year, yielding a larger discrepancy. Additionally,
447 one year at one site in the Southern NWT region was also an outlier. At this site the relatively
448 warm ground conditions during the freezing season led to a low n_f (0.1) during this year
449 compared to the other 12 years (0.46 on average). However, despite the warm winter conditions
450 the annual mean ground temperature remained comparable to the other years, only increasing
451 slightly. As a result, the TTOP model produced a larger error for this site during this year but
452 produced low error at this location for the remaining years.

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

465 **4.4 Sources of Uncertainty**

466 The methods used to rank the importance of variables have their own uncertainties that
467 could affect the reliability of the results. First, since the percentiles were derived from the
468 observed data the range of values for each parameter differed and would vary if a different
469 dataset was used. Second, although random forest is able to cope with highly correlated variables
470 for prediction (Boulesteix et al., 2012), there are conflicting conclusions on the reliability of
471 variable importance rankings (Strobl & Zeileis, 2008; Nicodemos et al., 2010; Tolosi &
472 Lengauer, 2011; Gregorutti et al., 2017). For this study, a majority of the input parameters are
473 highly correlated with at least one other parameter as some parameters are used to derive others
474 (Figures S4-6). This may have led the variable importance rankings of the random forest to be
475 unreliable when all parameters were used. Additionally, although the random forest model
476 using all variables performed relatively well (MSE 0.2 °C; variance explained 98%), the regional
477 models had lower percentages of variance explained (43 - 93 %) even though MSE was similar
478 (0.2 – 0.8 °C). This may have impacted the reliability of the variable importance rankings for
479 these models, as they may have accurately predicted ground temperature. Finally, it is important
480 to note that due to the nature of random forest, the variable importance rankings are not perfectly
481 repeatable. However, in several random forest runs the most important and least important
482 parameters were consistent even if they were not in the exact same order each time. Despite the
483 possible errors and uncertainty in the results of this, the variable importance analyses were in
484 general agreement for the two methods and supported findings from previous studies.

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

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

500 **4.5 Parameter classification recommendations**

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

510 Regionally, in locations where $FDD_a \gg TDD_a$, the impact of inadequate characterization
511 of n_t and r_k , was shown to be minimal. Therefore, more general assumptions and classifications

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

524 Finally, many studies that determine TTOP characterize r_k using vegetation, assigning
525 values between 0.0 and 1.0 (Smith & Riseborough, 1996; Riseborough & Smith, 1998; Way &
526 Lewkowicz, 2016; Obu et al., 2019; Garibaldi et al., 2021). However, recent studies (including
527 the data analyzed for this study) have shown r_k values exceeding 1.0 (Bevington & Lewkowicz,
528 2015; Lin et al., 2015; Zou et al., 2017). This likely occurs as a product of extremely dry
529 conditions in winter and higher soil moisture during summer, resulting in greater thermal
530 conductivity in the warm season. This is typically observed at sites with rocky or bedrock
531 substrates and limited vegetation cover and soil moisture (Lin et al., 2015; Luo et al., 2018). In
532 southern permafrost environments, the assumption of $r_k < 1$ at these sites (such as high elevation
533 rocky slopes, Fig. 2b) likely results in mischaracterization of the permafrost condition. The
534 varying sensitivity of the TTOP model to specific parameters in different environments

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

538 **5 Conclusions**

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

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

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

563 **Data Availability**

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

566 **Author Contributions**

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

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

571 RGW – Conceptualization, Funding Acquisition, Investigation, Methodology, Writing (review
572 and editing)

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

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

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

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

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

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

580 **Competing Interests**

581 The authors declare they have no competing interests

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