Thermal habitat of flowing waters in Ontario: Updated models to predict current and future stream temperatures

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Ministry of Natural Resources

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Thermal habitat of flowing waters in Ontario: Updated models to predict current and future stream temperatures

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Abstract

Water temperature influences the distribution, abundance, and health of aquatic organisms. As a result, an understanding of current and future temperatures is essential for effective resource management. Using a large stream temperature database, we developed models to predict July mean stream temperatures across Ontario. We then used a novel statistical approach to classify the thermal regime of each stream reach. Separate models were developed for the Mixedwood Plains (MWP) ecozone and the combined Ontario Shield and Hudson Bay Lowlands (OSD & HBL) ecozones. The OSD & HBL was further subdivided into small streams (upstream catchment area ≤700 km^2) and large rivers (upstream catchment area >700 km^2). The fitted models performed well, with cross-validated prediction errors between 1.09 and 2.20 °C. We used these models to predict current (1981–2010) July mean stream temperatures and thermal regimes for all stream reaches across Ontario. We also projected stream temperatures under climate change for three time periods (2011–2040, 2041–2070, 2071–2100) under two emissions scenarios representing intermediate and high greenhouse gas emissions (representative concentration pathways (RCP) 4.5 and 8.5). We found that Ontario is currently dominated by cold, cold-cool, and cool thermal regimes and that climate change will cause a shift towards a landscape dominated by cool, cool-warm, and warm thermal regimes. These changes will limit the availability of thermally suitable habitat for brook trout, with ~99% of all thermally suitable habitat lost by end of century under RCP 8.5. Predictions and projections produced using these models are suitable for management applications such as mapping thermally suitable habitat, identifying thermal refugia, stratifying streams for research and monitoring, and prioritizing conservation efforts.

Résumé

Habitat thermique des eaux vives en Ontario : modèles actualisés pour prévoir les températures actuelles et futures des cours d’eau

La température de l’eau influe sur la distribution, l’abondance et la santé des organismes aquatiques. Par conséquent, une compréhension des températures actuelles et futures est essentielle pour assurer une gestion efficace des ressources. À l’aide d’une vaste base de données sur les températures des cours d’eau, nous avons élaboré des modèles pour prédire les températures moyennes des cours d’eau en juillet dans l’ensemble de l’Ontario. Nous avons ensuite utilisé une nouvelle approche statistique pour classifier le régime thermique de chaque section de cours d’eau. Des modèles distincts ont été élaborés pour l’écozone des plaines à forêts mixtes et les écozones combinées du bouclier ontarien et des basses terres de la baie d’Hudson. Ces écozones combinées ont été subdivisées en petits ruisseaux (bassin versant en amont ≤700 km^2) et en grandes rivières (bassin versant en amont >700 km^2). Les modèles ajustés ont donné de bons résultats, avec des erreurs de prédiction ayant fait l’objet d’une validation croisée entre 1,09 et 2,20 °C. Nous avons utilisé ces modèles pour prédire les températures moyennes (1981-2010) des cours d’eau en juillet et les régimes thermiques pour toutes les sections de cours d’eau dans l’ensemble de l’Ontario. Nous avons également projeté les températures des cours d’eau sous l’effet des changements climatiques pour trois périodes (2011–2040, 2041–2070, 2071–2100) selon deux scénarios représentant des émissions intermédiaires et élevées de gaz à effet de serre (trajectoires de concentration représentatives [RCP pour *representative concentration pathway*], scénarios 4,5 et 8,5). Nous avons constaté que le territoire ontarien est actuellement dominé par des régimes thermiques froids, froids-froids et froids et que les changements climatiques entraîneront une transition vers un territoire dominé par des régimes thermiques froids, froids-chauds et chauds. Cette transition limitera la disponibilité d’habitats adaptés sur le plan thermique pour l’omble de fontaine, car ∼99 % de tous les habitats adaptés sur le plan thermique seront perdus d’ici la fin du siècle selon un scénario RCP 8,5. Les prédictions et les projections produites à l’aide de ces modèles conviennent à des applications de gestion comme la cartographie d’habitats adaptés sur le plan thermique, l’identification des refuges thermiques, la stratification des cours d’eau pour la recherche et la surveillance ainsi que la hiérarchisation des efforts de conservation par ordre de priorité.

Acknowledgements

We thank the many biologists, technicians, and summer students who sampled streams and shared stream temperature data. We greatly appreciate funding from the ministry’s Canada-Ontario Agreement on Great Lakes and the Integrated Monitoring Framework for Rivers and Streams. We thank Dan McKenney and colleagues from the Canadian Forest Service, Natural Resources Canada, who provided the air temperature grids used to model and project stream temperatures. Helpful reviews on an earlier version of this document were provided by Sarah Lewis and Emily Gryck of the ministry’s Policy Division and by Trevor Middel and Bob Metcalfe in Aquatic Research and Monitoring Section.

Contents

Introduction

Temperature has been described as a *master variable* and an *ecological resource* because of its influence on aquatic ecosystems (Brett 1971, Magnuson et al. 1979). Water temperature plays an important role in a variety of physical, chemical, and biological processes including nutrient cycling, ice dynamics, and the metabolism, growth, survival, and timing of life history events for fishes (Prowse 2001, Caissie 2006, Webb et al. 2008, Hasnain et al. 2010). Spatial and temporal variation in water temperature constrains the distribution and abundance of aquatic organisms in lotic systems (Vannote et al. 1980). As a result, a robust understanding of water temperature dynamics is required to manage and sustain ecological integrity in rivers and streams (hereafter referred to collectively as *streams*).

The natural and anthropogenic drivers of temperature dynamics in streams are well understood (Caissie 2006, Webb et al. 2008, Leach et al. 2023). Water temperature is controlled by complex and dynamic heat (energy) exchange processes. Incoming solar radiation, weather, hydrological conditions, channel morphology, and riparian land cover all affect temperature. Temperature at a given point along the stream network depends on local conditions and cumulative heat inputs from further upstream. As such, streams have characteristic longitudinal temperature increases from headwaters to outlet. Spatiotemporal variation in the factors driving stream temperatures lead to complex thermal regimes (i.e., the magnitude, frequency, duration, and timing of events such as seasonal minimums, means, or maximums) within and among watersheds (Maheu et al. 2016, Steel et al. 2017, Isaak et al. 2020).

Thermal regimes are frequently disrupted by anthropogenic activities such as deforestation and flow regulation (Caissie 2006, Webb et al. 2008). In recent decades, climate change has become an increasing concern due to evidence that the thermal suitability of stream habitat has already been altered (Isaak et al. 2010, Isaak et al. 2012, Ruesch et al. 2012). The biological implications of climate change include changes in physiology, behaviour, life history, and survival (Paukert et al. 2021). These changes will cause species distribution shifts, while warming creates conditions that can facilitate biological invasions (Rieman et al. 2007, Isaak et al. 2010, Paukert et al. 2021). Climate change will limit the availability of thermally suitable habitat for coldwater fishes, such as brook trout (*Salvelinus fontinalis*), while allowing warmwater fishes, such as smallmouth bass (*Micropterus dolomieu*), to expand into previously unsuitable habitat. For example, the range of brook trout may contract up to 49% and shift towards northeastern Quebec, while smallmouth bass could expand northward across Ontario (Chu et al. 2005). Understanding and predicting changes in thermal habitat under climate change is essential to guide management and sustain ecosystems into the future.

Thermal regime characterization is often based on limited temperature data collected within a single year (e.g., Stoneman and Jones 1996, Chu et al. 2009) or the temperature preferenda of fish present during sampling (e.g., Wichert and Lin 1996). However, inter-annual variation in the drivers of stream temperature make these snapshot approaches vulnerable to misclassification. Indeed, Jones and Schmidt (2018) found that more than 12 years of daily data can be needed to characterize thermal regimes. In recent years, widespread availability of low-cost, accurate, and reliable automated data loggers has facilitated extensive collection of long-term high-resolution temperature data (Johnson 2003, Jackson et al. 2016, Steel et al. 2017), allowing researchers to explore more robust thermal classification approaches that account for observed temperature variability (Rivers-Moore et al. 2013, Maheu et al. 2016, Jones and Schmidt 2018).

Despite the proliferation of data loggers, temperature measurements are usually only available for a few locations sparsely distributed across the landscape. These data gaps lead to inferential challenges because it is often unclear how to extrapolate temperature information upstream or downstream of a sampling site — particularly for small streams that rapidly increase in size and integrate increasingly heterogenous landscapes. As such, models that can predict temperatures at unsampled locations are of great value to researchers and resource managers. These models must be developed to provide information at a spatial scale relevant for resource management. Models that predict stream temperatures at regional scales are particularly useful because they can be applied to a range of management issues such as mapping thermally suitable habitat for fish, identifying thermal refugia, assessing anthropogenic impacts, and prioritizing conservation efforts (Gardner et al. 2003, Steen et al. 2008, Hill et al. 2013, Isaak et al. 2017). In recent years, regional-scale temperature models have been developed for many locations including Scotland (Jackson et al. 2018), Michigan and Wisconsin (Wehrly et al. 2009), New England (Detenbeck et al. 2016), and the northwestern United States (Isaak et al. 2017). Recent efforts have produced comprehensive temperature models for southern streams and larger rivers in northern Ontario (Jones et al. 2021), which are revisited here using newly collected stream temperature data and revised modelling covariates.

Our objective was to extend previous modelling work in southern Ontario by Jones et al. (2021) and Sutton and Jones (2021) to the entire province. We sought to develop temperature models to predict July mean stream temperatures under current and future climatic conditions. A novel approach first described by Jones et al. (2021) was applied to classify thermal regimes based on 30 years of historical climate data. This approach captures natural variability in thermal regimes and provides a robust understanding of thermal habitat available to biota. Predictions produced by these models can be used for several management purposes, including mapping thermally suitable habitat, identifying thermal refugia, and prioritizing conservation efforts.

Methods

Data collection

We assembled a stream temperature data set composed of long-term monitoring data and data contributed by external partners including conservation authorities and federal agencies (Figure 1). The initial data set was supplemented with targeted sampling at 402 sites between 2018 and 2022. These additional sites were selected to provide information on stream types insufficiently represented in the initial data set. In all cases, stream temperatures were recorded using digital data loggers that measured water temperatures a minimum of six times daily (average 96 times per day). Temperature records between July 1st and 31st were retained for analysis. We focused on July because this month is when stream temperatures typically peak in Ontario. July also represents the period of the year when temperature differences are most pronounced, and the availability of thermally suitable habitat can be limited for coldwater species. Our initial data set contained 7,256 July temperature records collected from 2,727 sites between 1989 and 2022.

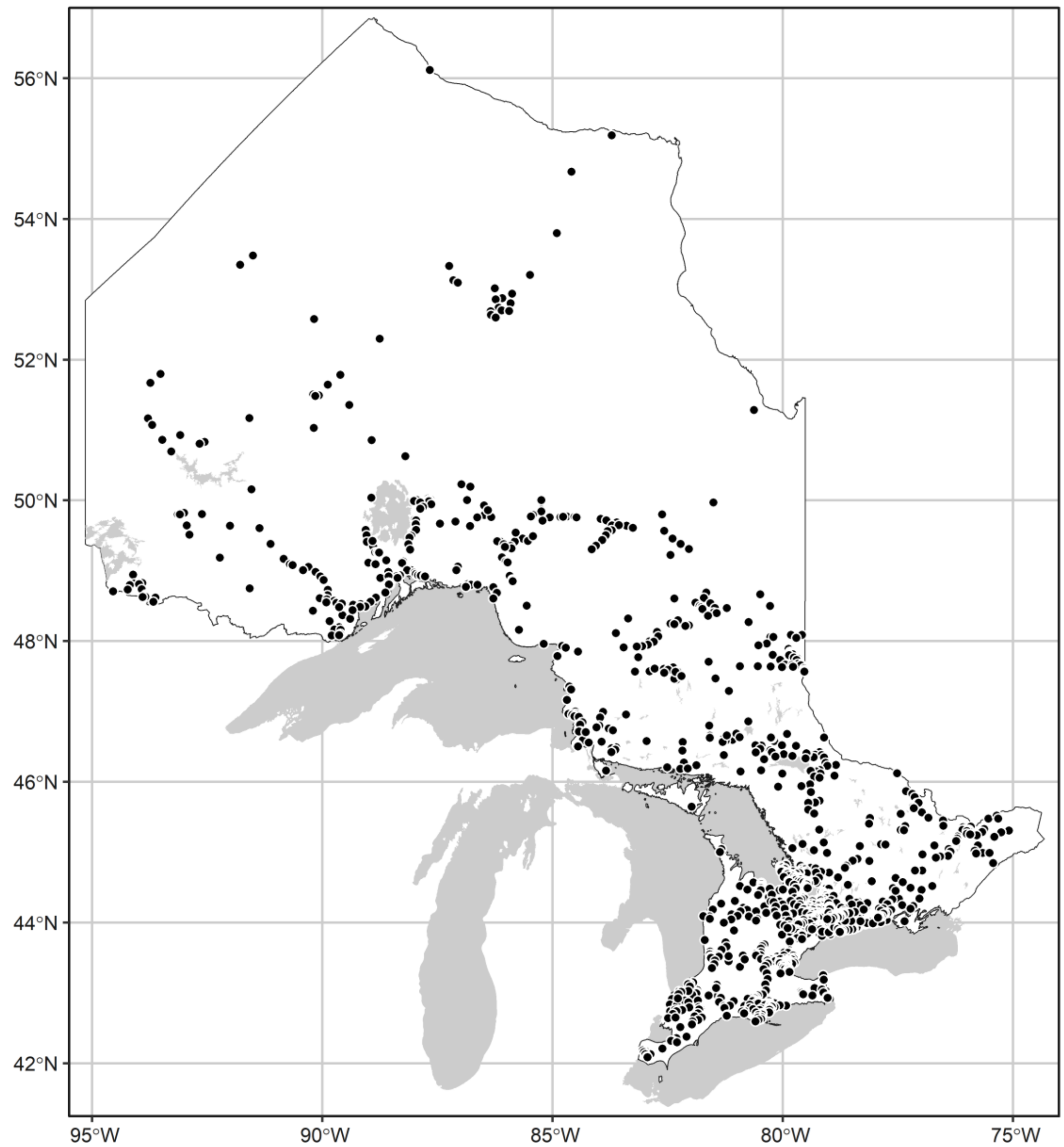

Figure 1. Stream temperature monitoring sites used to develop July mean stream temperature models in Ontario. Sites influenced by lakes, reservoirs, dams, and urbanization, as well as sites without useable water temperature data after quality control are not shown.

Sites were joined to the nearest stream reach in the provincial Aquatic Ecosystem Classification (AEC; Jones and Schmidt 2022). All sites with missing or invalid coordinates and sites that could not be definitively associated with a single reach were removed. In addition, sites influenced by lakes, dams, reservoirs, and urbanization were excluded from the data set. Lakes and reservoirs can increase stream temperatures by inundating downstream reaches with warmer epilimnetic water (Jones 2010, Leach et al. 2023). This warming effect often continues for many kilometres, with more rapid attenuation in smaller streams. The AEC provides a lake influence estimate for each stream reach as a function of upstream drainage and lake surface area, the distance from each lake outlet, and the spatial arrangement of tributaries (Jones and Schmidt 2022). This lake influence metric is further simplified into a binary classification of lake influenced (values ≥0.1) and not lake influenced (values <0.1). We excluded data from sites on reaches classified as lake influenced. Dams may also alter downstream water temperatures, typically through releases of cold hypolimnetic water (Ward 1985, Sinokrot et al. 1995). Sites near dams were identified and their time series discarded when temperature anomalies were evident. We also discarded data from highly urbanized sites (upstream catchment urbanization >25% and/or reach contributing area urbanization >50%) because stream temperatures are often artificially increased by warm run-off from impervious surfaces and increased exposure to solar radiation due to the removal of riparian vegetation.

Before modelling, the stream temperature data was quality controlled to eliminate anomalies caused by common problems such as drying during low flow, burial in sediment, and sensor failure. Additionally, some temperature records provided by external partners appeared to be inputted rather than measured. Time series with inputted measurements were excluded from further processing. After quality control, time series that covered less than 80% of July were discarded to ensure data used in modelling captured the range of variability in July temperatures. Before use, July mean stream temperatures were calculated from each time series by aggregating to daily means and then monthly means. This two-step aggregation was used to avoid bias in rare cases where the recording interval changed (e.g., from one minute to hourly intervals) partway through July. A subset of the data set provided by our partners (n=1,582 records) was provided as pre-aggregated July means and could not be quality controlled. During further cleaning and processing, we preferentially retained means derived from quality-controlled time series.

July mean stream temperatures were plotted against July mean air temperatures (see below for details of the air temperature data set) to identify anomalous records that were not detected in previous cleaning stages. We discarded years where the air-water temperature relationship was inconsistent with the overall trend following Jones et al. (2021). July mean stream temperatures were then aggregated at the reach scale in preparation for modelling. In cases where more than one site existed within a reach, we retained data from the site with the longest record and filled gaps or extended the time series with data from the remaining sites.

The final, cleaned, data set used for modelling comprised 3,697 July mean stream temperatures collected from 1,338 stream reaches (1,495 sites) between 1992 and 2022 (Figure 2A). Sampled reaches covered a variety of stream types and thermal regimes (Figure 2B). Mean record length was 2.8 years, ranging from one to twenty-one years with a median of one year (Figure 2C). The wide period covered by this data set should make our results robust to variation in temperature caused by climatic variability (e.g., cool and dry vs. warm and wet summers).

Model covariates

Covariates used to model stream temperature were identified based on a literature review, the results of previous models, exploratory data analyses, and professional judgement. We focused on covariates with continuous spatial coverage across Ontario that could be characterized using existing data sets. Covariates used in modelling were air temperature (T_A), upstream catchment area (UCA), baseflow index (BFI; Neff et al. 2005), overburden depth (Gao et al. 2007), and the percentage of treed and wetland cover. A description of each covariate and its expected effects on stream temperature are provided in Table 1.

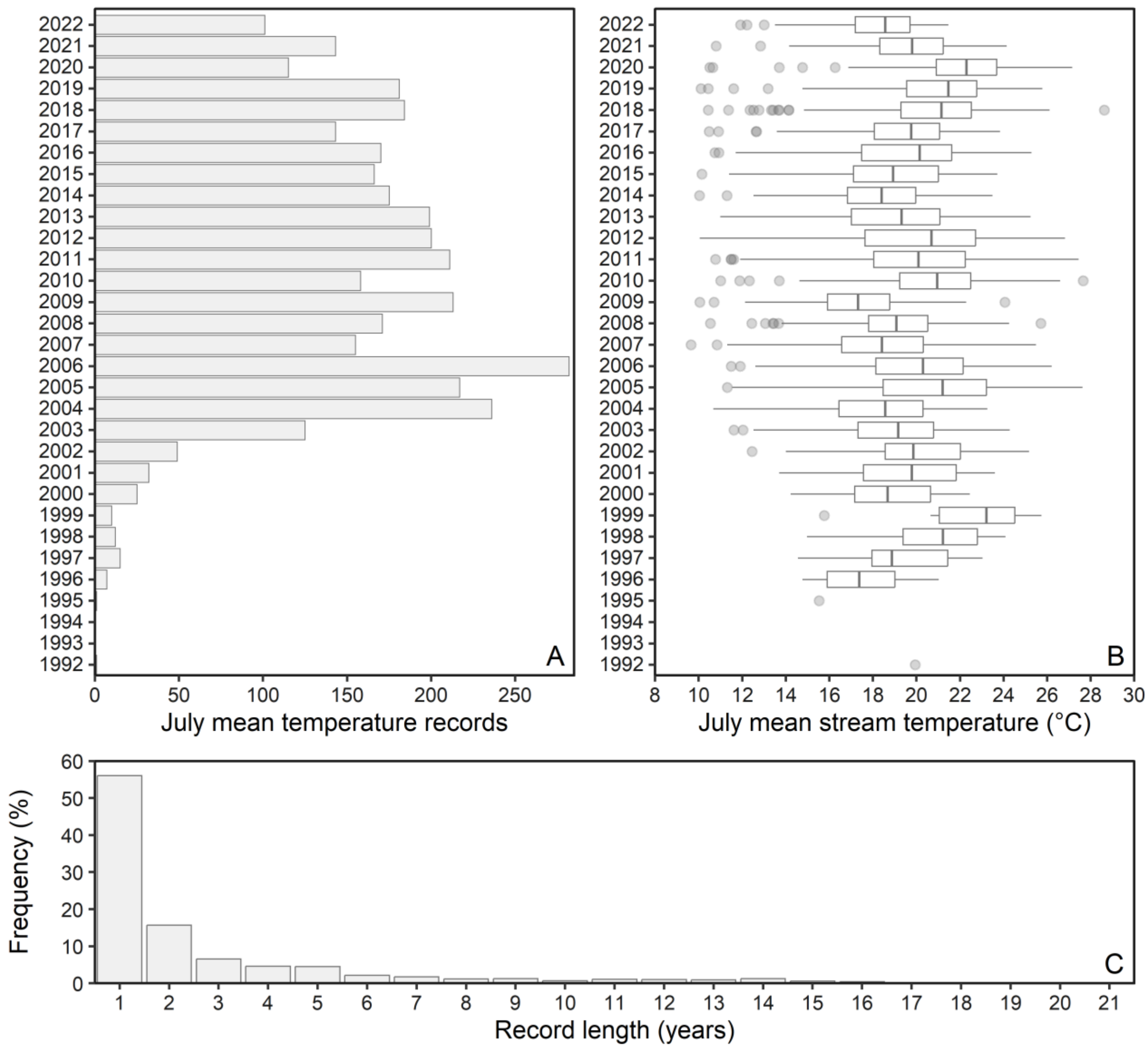

Figure 2. Temporal distribution of sampling effort (A), interannual variation in July mean stream temperatures (B), and record length distributions (C) of the final quality-controlled temperature modelling data set. Record lengths were calculated using the aggregated reach-scale data set.

Air temperatures were extracted from two gridded data sets of July minimum and maximum air temperatures obtained from the Canadian Forest Service. The first data set contained historical air temperatures for every year between 1980 and 2022. This historical data had a resolution of 60 arc-seconds and was generated using the methods described by McKenney et al. (2011). The second data set contained air temperature projections under climate change for each year from 2011 to 2100. The projections were generated using an ensemble of climate models (CanSEM2, MIROC-ESM-CHEM, CESM1-CAM5, HadGEM2-ES) bias corrected and statistically downscaled to a 300 arc-seconds resolution (McKenney et al. 2006, 2011). We obtained projections for two representative concentration pathway (RCP) scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions. Although previous analyses in Ontario included a low emissions scenario (RCP 2.6), it was not explored here because failure to curb greenhouse emissions makes this scenario increasingly unlikely (Sanderson et al. 2016, 2017). We calculated July mean air temperatures as the average of the minimum and maximum air temperature grids for each data set and year. July mean air temperatures were extracted for each stream reach as a weighted mean proportional to the stream length overlapping each air temperature grid cell.

Table 1. Covariates considered when modelling July mean stream temperatures across Ontario.

Covariate	Rationale	Units
Air temperature (T_A)	Air temperature is strongly correlated with incoming solar radiation — the primary component of stream heat budgets. Sensible heat transfer between the air and stream surface also affects water temperatures.	°C
Catchment area (UCA)	Larger, wider, streams are exposed to incoming solar radiation across greater lengths and less affected by riparian shading, which should result in warming.	km^2
Baseflow index (BFI)	Higher baseflow values are associated with increased groundwater inputs that should cool streams.	NA
Overburden depth	Greater depths of permeable materials are associated with increased groundwater transport and recharge.	m
Treed[1]	Riparian vegetation shades streams, reducing incoming solar radiation and resulting in colder temperatures.	%
Wetland[1]	Wetlands may be sources of warm surface water or cool groundwater depending on the context.	%

[1]These covariates are amalgamations of several land cover classes from the Ontario Land Cover Compilation (MNRF 2014). The treed land cover class encompasses the upland treed, deciduous treed, mixed treed, coniferous treed, cultivated treed, and hedge row classes. The wetland cover class encompasses the marsh, swamp, fen, bog, and treed peatland classes.

Upstream catchment area, baseflow index, overburden depth, and the percentage of treed and wetland land cover were extracted from the AEC base data. In the AEC, reach characteristics are summarized at four spatial scales (Figure 3): reach channel (RCh), reach contributing area (RCA), upstream channel (UCh), and upstream catchment area (UCA). In our preliminary data analyses, we found that covariates were strongly correlated across spatial scales, particularly in smaller streams. As a result, we retained data from all spatial scales for each covariate to identify the combination of spatial scales that generated the most accurate stream temperature predictions. See Jones and Schmidt (2017, 2022) for descriptions of covariate data sources and calculations.

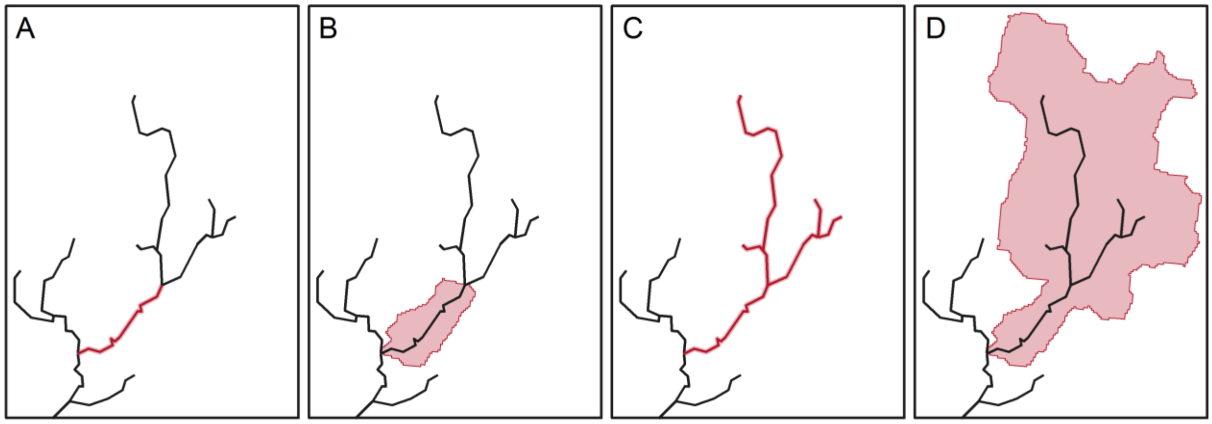

Figure 3. The spatial scales of landscape summary used in the Aquatic Ecosystem Classification: (A) reach channel (RCh), (B) reach contributing area (RCA), (C) upstream channel (UCh), and (D) upstream catchment area (UCA).

Temperature at any point along the stream network depends on local and upstream conditions, with conditions immediately upstream having the strongest influence (Caissie 2006, Webb et al. 2008, Leach et al. 2023). As a result, landscape summaries that use a “lumped” approach where all input raster grid cells are given equal weights may overestimate the influence of distant land cover. A more realistic approach is to incorporate a decay function that accounts for decreasing influence with increasing distance. Research shows that distance weighting land cover improves predictive performance when modelling stream health (King et al. 2005, Van Sickle and Johnson 2008, Peterson et al. 2011, Walsh and Webb 2014). Distance weighting has also been applied to stream temperature modelling, albeit without comparison to lumped metrics (Isaak et al. 2010, Hill et al. 2013). We calculated distance weighted baseflow index, treed, and wetland covariates and compared predictive performance with their lumped counterparts extracted from the AEC.

Distance weights were calculated using a hydrologically enforced digital elevation model (DEM) with a 30-metre resolution. The DEM and its derivative products are part of the data underlying the AEC. A D8 flow direction pointer grid (O’Callaghan and Mark 1984) generated from the DEM was used to generate flow paths, calculate flow accumulation, and identify streams. We applied a two-component distance weighting model that models the influence of each raster grid cell as a decreasing function of the distance between the grid cell and a specific location on the stream (Johnson et al. 2007, Van Sickle and Johnson 2008). In a two-component model, the weight (w_i) of a grid cell is calculated as $f_T(d_T, \alpha_T)\, f_I(d_I, \alpha_I)$, where d_T and d_I are to-stream and in-stream flow path distances and α_T and α_I are parameters controlling the distance over which influence declines. The weighted mean for continuous covariates (e.g., baseflow index) is then given by:

$$X(\alpha_T, \alpha_I) = \frac{\sum_{i=1}^{n} k_i f_T(d_{Ti}, \alpha_T) f_I(d_{Ii}, \alpha_I)}{\sum_{i=1}^{n} f_T(d_{Ti}, \alpha_T) f_I(d_{Ii}, \alpha_I)}$$

where k_i is the value of the ith raster cell in the upstream catchment of the location of interest, and d_{Ti} and d_{Ii} are flow path distances to the stream and catchment outlet from the raster cell. For categorical covariates (e.g., land cover), weighted proportion is calculated by substituting k_i with an indicator function $I(k_i)$ that has a value of 1 if the covariate of interest occurs in the ith raster cell and 0 otherwise.

We modelled decline in influence with increasing distance using linear, inverse, and exponential functional forms (Table 2), which were chosen because they have been used in previous studies (King et al. 2005, Van Sickle and Johnson 2008, Peterson et al. 2011, Walsh and Webb 2014) and represent a range of attenuation shapes (Figure 4). The rate parameter (α) has a different meaning for each functional form, thus we report the half-decay distance (Van Sickle and Johnson 2008, Walsh and Webb 2014) to aid interpretation. Half-decay distances represent the distance over which influence declines to half its initial value. Standardizing using half-decay distances also makes comparisons between functional forms more intuitive because differences result primarily from the shape of the attenuation curve. We hypothesized that influence would decline faster over land than within the stream, thus we explored different half-decay distances for the to-stream (50 m, 100 m, 200 m, 400 m, 800 m, and 1600 m) and in-stream (500 m, 1 km, 2 km, 4 km, 8 km, and 16 km) components of the weighting function. We assessed all functional form and half-decay distance permutations at each stream reach. To-stream and in-stream flow path distances were calculated from the downstream end of each reach. An illustrative example of distance weighting is provided in Figure 5.

Table 2. Equations used to calculate weightings (w_i) and half-decay distances (HD) for distance weighted covariates. α is a rate parameter with a unique meaning for each functional form. d is the distance between a raster grid cell and the catchment outlet or stream for a given location.

Functional form	Equation	Half-decay distance
Linear	$w_i = \begin{cases} 1 - \alpha d, & \alpha d \leq 1 \\ 0, & \alpha d > 1 \end{cases}$	$HD = -0.5\alpha$
Inverse	$w_i = (d+1)^{-\alpha}$	$HD = 0.5^{\frac{-1}{\alpha}} - 1$
Exponential	$w_i = e^{-\alpha d}$	$HD = \frac{log_e(0.5)}{\alpha}$

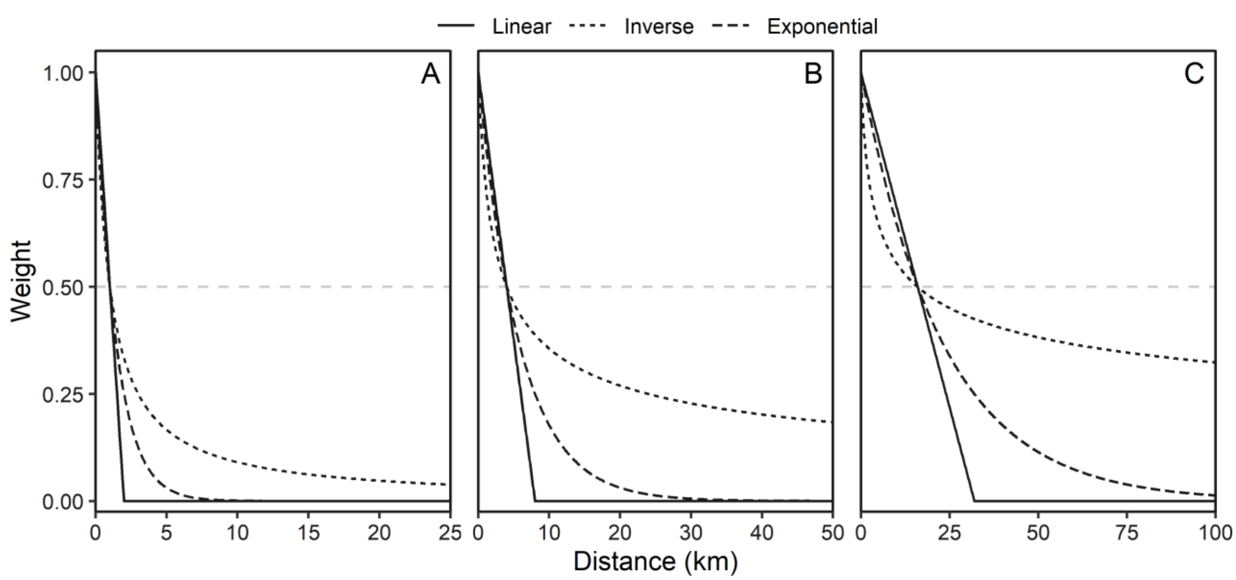

Figure 4. Examples of linear, inverse, and exponential decay at three half-decay distances: (A) 1 km, (B) 4 km, and (C) 16 km. The intersection of the curves and horizontal dashed lines highlight the downstream distance where weights reach 0.5 (i.e., the half-decay distance).

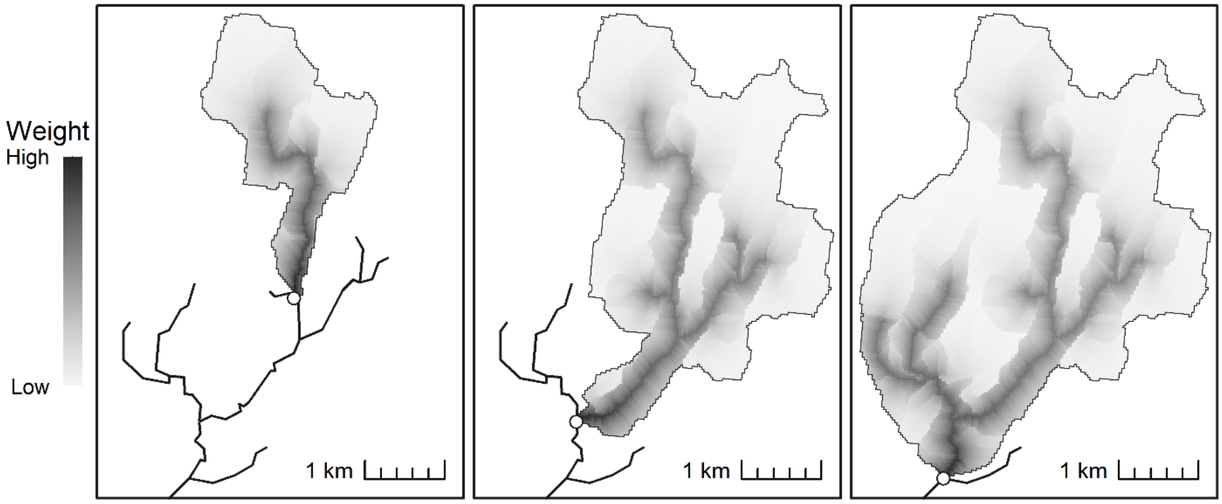

Figure 5. Distance weights calculated for three locations on a stream network. In this example, a two-component distance weighting model with an inverse functional form and to-stream and in-stream half-decay distances of 200 m and 8 km was applied. Circles indicate locations on the network used to calculate to-stream and in-stream flow path distances in each example.

Model development

Water temperature can be modelled using process-based and statistical methods (Caissie 2006, Dugdale et al. 2017). Process-based methods simulate stream energy budgets to produce highly accurate temperature predictions. However, these simulations require extensive site-scale data for calibration, limiting their utility at broader spatial scales. In contrast, statistical approaches model relationships between empirical stream temperature data and covariates correlated with energy exchange processes (e.g., air temperature). Statistical models require less site-scale data than process-based models, making them more suitable when predictions are needed over larger areas (Wehrly et al. 2009, Isaak et al. 2010, Dugdale et al. 2017). As a result, we modelled July mean stream temperatures using statistical models because we sought to make predictions across Ontario. Specifically, we used linear mixed models to approximate relationships between July mean stream temperature (T_W) and our covariates of interest. Linear mixed models include both fixed and random effects, making it possible to model hierarchical data sets where records within a sampling unit are not independent (Bolker et al. 2009, Harrison et al. 2018). In our data set, many reaches were sampled over multiple years, violating independence assumptions. Therefore, we included a random intercept for each reach in all models to account for variation across years that was not accounted for by the fixed effects of covariates. All models were fit by restricted maximum likelihood using the lme4 package (Bates et al. 2015) and R version 4.3.2 (R Core Team 2023).

Jones et al. (2021) previously found that correlations between stream temperature and covariates (e.g., air temperature) varied with stream size, climate, and geology. Further, preliminary analyses suggested that it would be impossible to develop an accurate temperature model for Ontario as a whole (i.e., the predictive error was too large). As a result, we developed separate temperature models for the Mixedwood Plains (MWP) ecozone and combined Ontario Shield and Hudson Bay Lowland (OSD & HBL) ecozones. The OSD & HBL were modelled together due to their relative proximity and a paucity of temperature data for the HBL (Table 3). The OSD & HBL were further stratified into small stream (UCA ≤700 km^2) and large river (UCA >700 km^2) models based on evidence that stream and air temperatures were increasingly correlated as catchment size increased (Figure 6). Reaches crossing ecozone boundaries were assigned to the ecozone containing the majority of their upstream catchment.

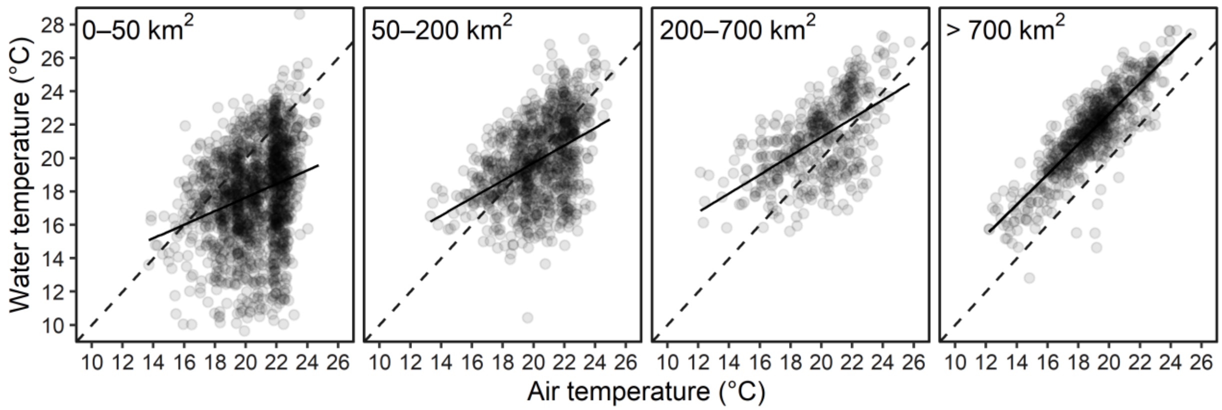

Figure 6. Correlations between July mean air (T_A) and water (T_W) temperatures across drainage sizes for Ontario streams. The dashed lines are identity lines, while the solid lines represent the relationship between air and water temperatures fit using ordinary least squares regression.

Table 3. Distribution of sampling effort by ecozone and stream size class (defined by upstream catchment area (UCA); small streams = UCA ≤700 km^2; large rivers = UCA >700 km^2) in the final quality-controlled stream temperature modelling data set. The number of sites and reaches sampled differs because multiple sites may occur within a single reach. Record lengths were calculated from the aggregated reach-scale data set.

Ecozone	Size	Sites	Reaches	Record length (years)
Mixedwood Plains	All	935	822	2,424
Ontario Shield	Large rivers	126	108	560
	Small streams	420	394	681
Hudson Bay Lowlands	Large rivers	4	4	12
	Small streams	10	10	20

We defined several models *a priori* to identify the combination of covariates that best predicted T_W (Table 4). This candidate set included a simple model that included only the effect of T_A, a full model with all predictors, and reduced models to assess other covariates in conjunction with T_A. Where applicable, we also included interactions between T_A and UCA, T_A and BFI, and UCA and the treed land cover percentage, allowing us to explore possible relationships such as greater warming of wide rivers and rivers exposed to solar radiation over longer lengths ($T_A \ x \ UCA$), higher thermal inertia in colder streams with larger groundwater inputs ($T_A \ x \ BFI$), and the reduced influence of riparian shading as rivers become larger and wider ($UCA \ x \ treed$).

We evaluated all interaction combinations (i.e., no interactions, one, two, or three interactions) and excluded any interactions that did not improve model performance.

Table 4. Linear mixed model structures explored to predict July mean stream temperature (T_W) across Ontario. Where applicable, all combinations of interactions between T_A and UCA, T_A and BFI, and UCA and percentage treed land cover were explored. See Table 1 for detailed covariate descriptions.

Model	Formula
1	T_A
2	$T_A + UCA$
3	$T_A + UCA + BFI$
4	$T_A + UCA + BFI + treed$
5	$T_A + UCA + BFI + treed + wetland$
*6	$T_A + UCA + BFI + overburden$
*7	$T_A + UCA + BFI + overburden + treed$
*8	$T_A + UCA + BFI + overburden + treed + wetland$

* These models were fit for the Mixedwood Plains sub-model only.

Models were initially fit using the unweighted covariates extracted from the AEC to identify the combination of covariates and spatial summary scales that produced the optimal model. Due to collinearity between spatial scales, each covariate was restricted to one spatial scale per model. For example, a model could include both UCA BFI and RCA treed land cover, but not both UCA and RCA BFI. After identifying the optimal unweighted model, we applied the iterative selection method used by Walsh and Webb (2014) to determine if including distance weighted covariates improved model performance. In brief, all weighted permutations of a covariate are substituted into the optimal unweighted model to determine the optimal weighting scheme. This weighting scheme is then used to identify an optimal partially weighted model structure. This procedure is repeated, using the partially weighted model from the previous step as a starting point, until all covariates have been weighted and an optimal fully weighted model is identified. We optimized BFI first, followed by percentage treed land cover, and finally percentage wetland land cover.

Model performance was assessed using repeated k-fold cross-validation with 10 repeats and 10 folds. Folds were stratified by reach (i.e., all data from a reach occurred in a single fold) to avoid underestimating prediction error (Roberts et al. 2017). Predictive performance was summarized using root mean square error (RMSE) and bias. RMSE is given by: $RMSE = \sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/n}$ where $\hat{y}_i$ and y_i are observed and predicted stream temperatures for a reach and year, and n is the total number of reach-year combinations. Bias was calculated as: $bias = \sum_{i=1}^{n}(y_i - \hat{y}_i)/n$. RMSE and bias were calculated for each repeat and then averaged to generate an overall score. The model with the lowest cross-validation RMSE was initially chosen as the optimal model. We then inspected model coefficients, discarding the model in favour of the model with the second lowest RMSE if the coefficients did not match theory (e.g., BFI was expected to have a negative coefficient due to the cooling effect of groundwater and a model with a positive BFI coefficient would be discarded). For models with interactions, we plotted interactions to assess conformity with our hypothesized effects (see Table 1 above). We repeated this process until we identified a model where all coefficients and interactions were valid.

Prediction and classification

Thermal classification is challenging because stream temperature can vary considerably through time and space. The thermal regime of a stream reach is often determined using a single year of data or a prediction based on the average conditions over a given period (e.g., a 30-year climate normal). However, this approach is vulnerable to misclassification because it fails to account for inter-annual variation (Jones and Schmidt 2019). A more robust approach is to use several years of data to construct probability distributions to determine the probability that temperature falls within a given class (Figure 7; Jones and Schmidt 2019, Jones et al. 2021). We used the five-class approach developed by Jones et al. (2021) to classify the thermal regime of every stream reach. This approach establishes the affinity of each reach to one of three thermal classes: cold (<18.5 °C), cool (18.5–21.5 °C), and warm (>21.5 °C). Reaches falling within one of these classes >80% of the time are assigned to that class, while all other reaches are assigned to a cold-cool or cool-warm transitional class (Figure 7; Appendix 1). An overview of the development and application of this probabilistic approach was detailed by Jones and Schmidt (2019) and Jones et al. (2021).

Thermal Class	Class Membership Probability		
	Cold (≤ 18.5 °C)	Cool (18.5–21.5 °C)	Warm (≥ 21.5 °C)
Cold	1.00	0.00	0.00
	0.99	0.01	0.00
	0.97	0.03	0.00
	0.89	0.11	0.00
Cold-Cool	0.73	0.27	0.00
	0.50	0.50	0.00
	0.27	0.73	0.00
Cool	0.10	0.89	0.01
	0.03	0.94	0.03
	0.01	0.89	0.10
Cool-Warm	0.00	0.73	0.27
	0.00	0.50	0.50
	0.00	0.27	0.73
Warm	0.00	0.11	0.89
	0.00	0.03	0.97
	0.00	0.01	0.99
	0.00	0.00	1.00

Figure 7. An overview of the thermal classification framework from Jones et al. (2021). Thermal class is determined by the probability of membership to a given core class (cold, cool, or warm). Class membership occurs when the probability exceeds a threshold, in this case p>0.8. When a reach fails to meet this threshold, it is assigned to a transitional class (illustrated by grey bands). See Jones and Schmidt (2019) and Jones et al. (2021) for a detailed overview of this framework.

July mean stream temperatures were predicted for each year between 1981 and 2010 using the optimized temperature model for each region (i.e., MWP, OSD & HBL small streams, OSD & HBL large rivers). The mean and standard deviation of these predictions were then used as inputs to calculate class probabilities and assign thermal regimes following the methods described above. We also projected July mean stream temperatures under moderate (RCP 4.5) and high (RCP 8.5) greenhouse gas emissions over three time periods referred to in this report as the 2030s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100). Thermal regimes for each scenario and time period were classified using the same methods applied to the baseline period (1981–2010).

We mapped stream temperature and thermal class predictions for the baseline period to better understand current thermal habitat across Ontario. Temperature anomalies relative to baseline were mapped for each climate scenario to explore spatiotemporal temperature trends. We also evaluated changes in thermally suitable habitat availability for brook trout and smallmouth bass to illustrate the effects of climate change. Following Sutton and Jones (2021), July mean stream temperatures <18.5 °C defined thermally suitable brook trout habitat, while temperatures >21 °C delineated suitable smallmouth bass habitat. Temperatures between 18.5 °C and 21 °C were considered marginal habitat for both species. For both species, we summarized thermal habitat availability, and the number and size of suitable habitat patches (i.e., a group of flow-connected reaches representing thermally suitable habitat) at the provincial scale.

Results

Temperature modelling

The optimized unweighted and weighted models predicted July mean stream temperature with similar accuracy (Table 5). Excluding the OSD & HBL large river model, covariate coefficients and interactions matched theory (Table 1) in the best performing unweighted and weighted models. For OSD & HBL large rivers, the best performing model with valid coefficients was the simple air temperature only model using both unweighted and weighted covariates. As a result, we report a single set of results for OSD & HBL large rivers to avoid repetition.

The optimal weighted models for the MWP and OSD & HBL small streams both included BFI and treed land cover (Table 6). In both models, the parameter values for BFI corresponded to a wide riparian corridor extending many kilometres upstream. The decay functions' linear nature means that the influence of BFI declines to zero at 3200 metres along overland flow paths or 32 kilometres upstream. Contrasting with BFI, the parameter values for treed land cover represent a narrow riparian corridor extending tens of kilometres upstream. Indeed, this riparian buffer was only 100 metres wide for MWP streams and 200 metres wide for OSD & HBL small streams. The non-linear nature of the in-stream decay functions means the influence of treed land cover extends farther upstream than BFI. Weighted wetland cover appears only in the optimal OSD & HBL small streams model. Parameter values corresponded to a linear decline to zero over 1600 metres overland, with an upstream domain similar to treed land cover (i.e., tens of kilometres).

Given the comparable performance of unweighted and weighted models for the MWP and OSD & HBL small streams, we visually compared mapped output from the unweighted and weighted models to determine if the added complexity of distance weighting was justified given marginal performance improvements. Although performance was comparable, there were differences in spatial distribution and longitudinal patterns of the temperature predictions between weighted and unweighted models. In general, the weighted models produced more realistic predictions matching expected longitudinal temperature patterns and known thermal regimes. As a result, the optimal weighted models were used to predict and forecast stream temperatures for the MWP and OSD & HBL small streams. The structure and coefficients of the final models used to predict and forecast July mean stream temperatures are given in Table 7.

Table 5. Model performance of July mean stream temperature models fit for Ontario streams using unweighted and weighted covariates. Root mean square error (RMSE) and bias were calculated with repeated k-fold cross-validation. Models were fit separately for the Mixedwood Plains (MWP) ecozone and combined Ontario Shield and Hudson Bay Lowland (OSD & HBL) ecozones. The OSD & HBL were further stratified into small streams (≤700 km^2) and large rivers (>700 km^2). The optimal model for OSD & HBL large rivers was the same using either unweighted or weighted covariates.

Ecozone	Model	Weighting	RMSE (°C)	Bias (°C)
MWP	All	Unweighted	2.21	-0.04
		Weighted	2.20	-0.02
OSD & HBL	Small streams	Unweighted	1.84	-0.03
		Weighted	1.82	-0.03
	Large rivers	Unweighted/weighted	1.09	-0.03

Table 6. Weighting schemes of the optimal weighted July mean stream temperature models for the Mixedwood Plains (MWP) ecozone and small streams (≤700 km^2) for the combined Ontario Shield and Hudson Bay Lowlands (OSD & HBL) ecozones. Baseflow index (BFI), treed land cover ($treed$), and wetland cover ($wetland$) were weighted using two-component distance weighting functions. Half-decay distances (HD) and functional forms were chosen for each covariate using the iterative selection approach described by Walsh and Webb (2014).

Ecozone	Model	Covariate	Weighting scheme
MWP	All	BFI	To-stream: HD = 1600m; form = linear
			In-stream: HD = 16 km; form = linear
		$treed$	To-stream: HD = 50 m; form = linear
			In-stream: HD = 16 km; form = inverse
OSD & HBL	Small streams	BFI	To-stream: HD = 1600 m; form = linear
			In-stream: HD = 16 km; form = linear
		$treed$	To-stream: HD = 100 m; form = linear
			In-stream: HD = 16 km; form = exponential
		$wetland$	To-stream: HD = 800 m; form = linear
			In-stream: HD = 16 km; form = inverse

Table 7. Fixed effect parameter estimates (β), standard errors (SE), and confidence intervals for the linear mixed models used to predict July mean stream temperatures. Separate models were fit for the Mixedwood Plains (MWP) ecozone and the combined Ontario Shield and Hudson Bay Lowland (OSD & HBL) ecozones. The OSD & HBL was further stratified into small streams (≤700 km²) and large rivers (>700 km²). Covariates were not standardized, and the coefficients can be interpreted as the change in July mean stream temperature for a unit change in each covariate.

Ecozone	Model	Term	β ± SE	95% confidence interval	
				Lower	Upper
MWP	All	Intercept	1.75 ± 1.00	-0.21	3.7
		T_A	0.96 ± 0.04	0.88	1.05
		UCA	0.002 ± 0.0002	0.001	0.002
		BFI[1]	8.12 ± 2.00	4.20	12.05
		$overburden$[2]	-0.02 ± 0.002	-0.02	-0.01
		$treed$[1]	-0.05 ± 0.006	-0.07	-0.04
		$wetland$[2]	0.05 ± 0.01	0.03	0.07
		$T_A\ x\ BFI$	-0.58 ± 0.09	-0.76	-0.41
OSD & HBL	Small streams	Intercept	6.58 ± 0.64	5.33	7.82
		T_A	0.77 ± 0.02	0.73	0.81
		UCA	0.006 ± 0.0008	0.005	0.008
		BFI[1]	-1.28 ± 0.85	-2.93	0.37
		$treed$[1]	-0.02 ± 0.006	-0.03	-0.01
		$wetland$[1]	-0.02 ± 0.007	-0.04	-0.01
	Large rivers	Intercept	4.10 ± 0.37	3.38	4.84
		T_A	0.94 ± 0.02	0.90	0.98

[1]These covariates were weighted using a two-component distance weighting function. See Table 5 for details.

[2]These covariates were unweighted. Metrics were calculated at the RCA scale (overburden) or UCA scale (wetland).

Temperature predictions

Predicted July mean stream temperatures for the baseline period (1981–2010) ranged between 10.0 °C and 38.0 °C (Figure 8A). Excessively warm predictions (>25.0 °C) were rare, representing <0.1% of all predictions. There was substantial heterogeneity in predicted stream temperatures across the province, with evident spatial associations between stream temperature and climatic gradients, geologic landforms, and landscape characteristics. Temperatures generally decreased from south to north following natural gradients in air temperature and incoming solar radiation. In southern Ontario, colder streams were associated with regions of higher groundwater supply such as the Oak Ridges Moraine, northern Niagara Escarpment, and Norfolk Sand Plain. Warmer temperatures were commonly observed on the southwestern and southeastern clay plains, and in the mainstems of larger southern rivers such as the Grand and Thames. In northern Ontario, temperatures exceeding 20.0 °C were generally associated with lake outlets.

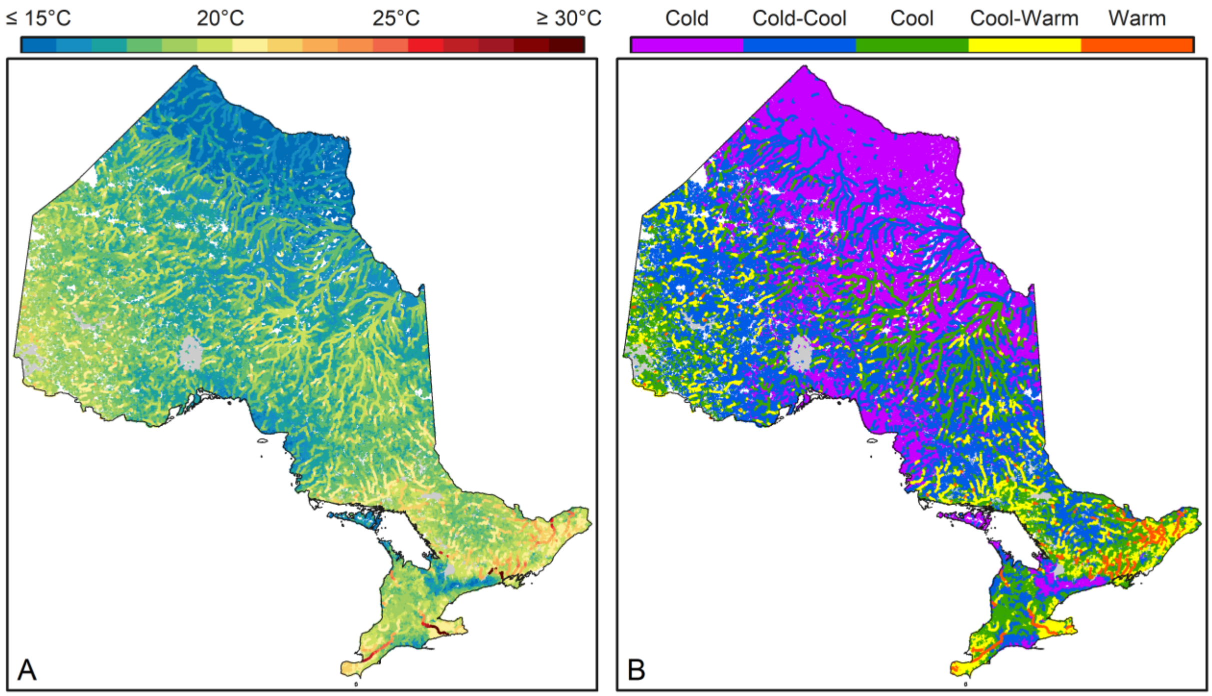

Figure 8. Predicted July mean stream temperatures (A) and thermal regimes (B) across Ontario for the baseline period (1981–2010). Thermal regimes were classified using a probability-based approach. See methods section and Jones et al. (2021) for an overview of the thermal classes.

Cold, cold-cool, and cool thermal regimes dominate across Ontario, representing roughly 89.5% of total provincial stream length (Figure 8B, Table 8). Warm and cool-warm thermal regimes are less common, and two-thirds of reaches with these thermal regimes are lake outlets. In general, large continuous patches of cool-warm and warm habitat were limited to southern Ontario. The north contained many large cold-cool and cool rivers, while larger rivers were often classified as cool-warm or warm in the south. Headwaters were predominantly associated with cold or cold-cool thermal regimes across Ontario.

Climate change projections

July mean stream temperatures are projected to increase substantially over the coming century (Figure 9). Projected warming was similar under both climate scenarios during the 2030s before diverging over subsequent periods. Under RCP 8.5, temperatures will rise faster over the 2050s and result in higher temperatures by end of century. Streams with treed riparian corridors and higher baseflows are projected to warm more slowly and remain colder further into the future. Conversely, large unshaded rivers, lake outlets, and streams with low baseflows are projected to warm rapidly. Headwater streams on glacial landforms such as the Oak Ridges Moraine will represent the final vestiges of coldwater habitat in Ontario.

In either scenario, streams with cold or cold-cool thermal regimes will be rare by end of century (Table 8). The loss of cold thermal regimes will be rapid, with projected declines nearing 50% by the 2030s in both scenarios. Coldwater stream length will decrease between 83% (RCP 4.5) and 99% (RCP 8.5) by the 2080s. Although cool and cool-warm thermal regimes will be common into the 2050s, warm thermal regimes will dominate the landscape by the 2080s. These changes will increasingly pressure brook trout as thermally suitable habitat declines, with ~99% of thermally suitable habitat lost by the end of century under RCP 8.5 (Table 9, Figure 10). Habitat losses will be smaller, but still severe, under RCP 4.5 (~83%). Thermally suitable brook trout habitat will be largely confined to the headwaters of Lake Ontario tributaries along the Oak Ridges Moraine and northern streams along the Hudson Bay coast. The number of brook trout habitat patches decreased substantially across all scenarios and time periods (Table 10), while streams became increasingly thermally suitable for smallmouth bass.

Table 8. Projected changes in the thermal regimes of Ontario streams under two representative concentration pathway (RCP) climate change scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions. See the methods section for an overview of the thermal classes and the probability-based approach used to classify thermal regimes.

Scenario	Period	Stream length (km)				
		Cold	**Cold-cool**	**Cool**	**Cool-warm**	**Warm**
Baseline	1981–2010	212,907	168,860	64,363	25,043	4,132
RCP 4.5	2011–2040	110,796	97,447	187,145	47,606	32,326
	2041–2070	60,574	43,273	205,045	84,353	82,075
	2071–2100	36,345	36,037	161,192	113,313	128,433
RCP 8.5	2011–2040	94,815	93,125	194,525	55,932	36,923
	2041–2070	31,274	45,654	125,479	143,985	128,927
	2071–2100	267	3,485	28,425	81,022	362,121

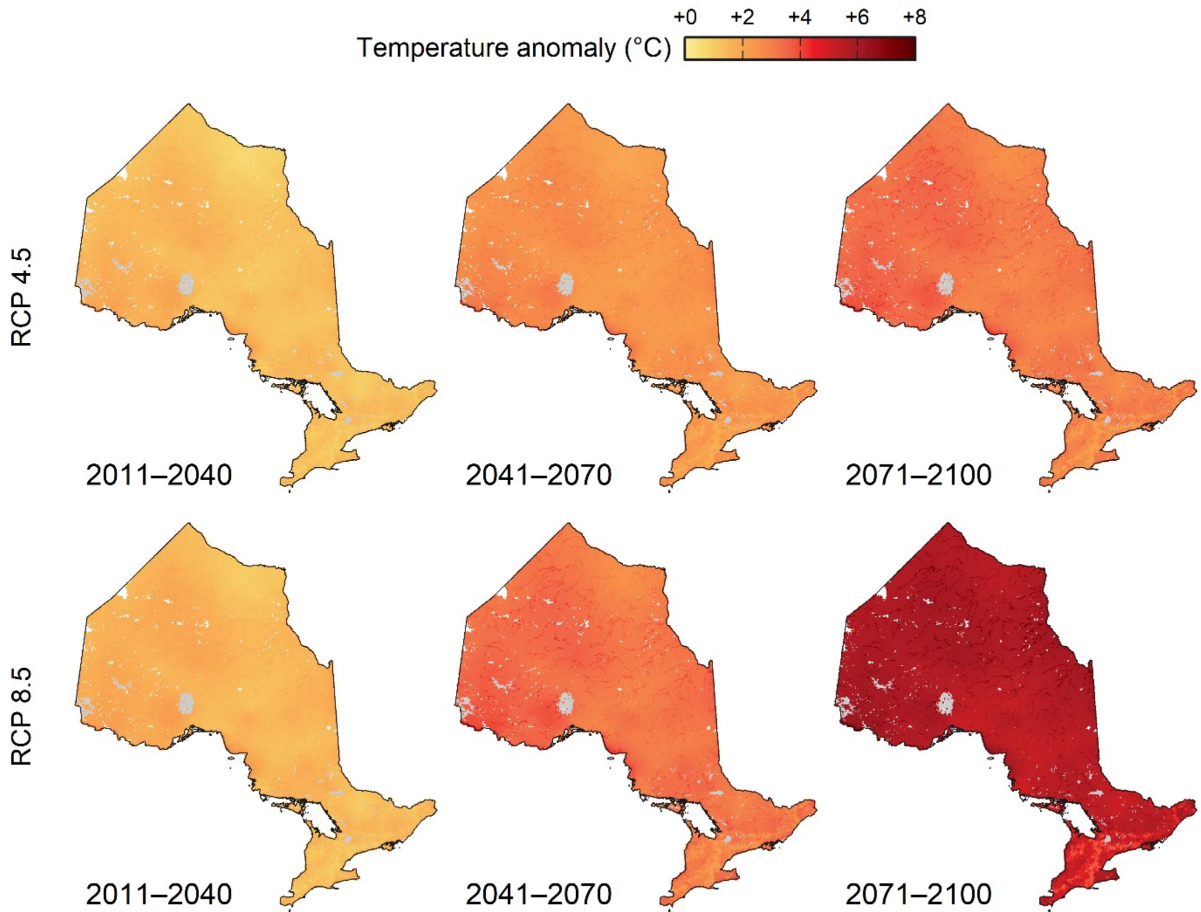

Figure 9. Projected temperature anomaly relative to baseline (1981–2010) for Ontario streams under two representative concentration pathway (RCP) climate change scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions.

Table 9. Projected changes in the thermal regimes of Ontario relative to the baseline period (1981–2010) streams under two representative concentration pathway (RCP) climate change scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions. See the methods section for an overview of the thermal classes and the probability-based approach used to classify thermal regimes.

Scenario	Period	Change from baseline (%)				
		Cold	Cold-cool	Cool	Cool-warm	Warm
RCP 4.5	2011–2040	-48.0	-42.3	+190.8	+90.1	+682.3
	2041–2070	-71.5	-74.4	+218.6	+236.8	+1,886.3
	2071–2100	-82.9	-78.7	+150.4	+352.5	+3008.3
RCP 8.5	2011–2040	-55.5	-44.9	+202.2	+123.3	+793.6
	2041–2070	-85.3	-73.0	+95.0	+475.0	+3020.2
	2071–2100	-99.9	-97.9	+55.8	+223.5	+8663.8

Table 10. Projected availability of suitable thermal habitat for brook trout and smallmouth bass in Ontario streams under two representative concentration pathway (RCP) climate change scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions. Brook trout habitat was defined as temperatures <18.5 °C, while smallmouth habitat was defined as temperatures >21.0 °C. Habitat patches are flow-connected reaches with thermally suitable habitat.

Species	Scenario	Period	Patches	Habitat (km)	Patch size (km)	
					Mean	Max
Brook trout	Baseline	1981–2010	150,315	310,784	2.07	3,654.39
	RCP 4.5	2011–2040	72,933	152,348	2.09	1,505.29
		2041–2070	38,958	78,959	2.03	174,77
		2071–2100	28,357	52,682	1.86	174.77
	RCP 8.5	2011–2040	63,846	132,639	2.07	1,301.83
		2041–2070	28,310	52,747	1.86	174.77
		2071–2100	459	444	0.98	9.37
Smallmouth bass	Baseline	1981–2010	3,685	20,865	5.66	805.73
	RCP 4.5	2011–2040	27,895	79,647	2.86	2,595.07
		2041–2070	70,642	162,738	2.30	5,890.73
		2071–2100	104,810	237,085	2.62	9,439.56
	RCP 8.5	2011–2040	33,049	90,109	2.73	3,969.74
		2041–2070	110,960	251,904	2.27	10,914.92
		2071–2100	174,441	427,592	2.45	24,235.53

Discussion

Temperature modelling

Our modelling approach was guided by knowledge of the processes, patterns, and spatial scales affecting stream temperatures. Through exploratory analyses, we identified distinctive patterns that reflect differing processes influencing stream temperature at various spatial scales. Smaller streams have small drainages that often encompass a single geology or landcover type (Jones et al. 2021). As drainage size increases, streams incorporate increasingly heterogenous landscapes and trend towards a common, average, condition. As a result, temperatures in large rivers are driven by fewer factors — with air temperature dominating at larger drainage sizes (>700 km^2). For the OSD & HBL, developing separate models based on drainage size reduced modelling complexity and improved the predictive performance of the final temperature models.

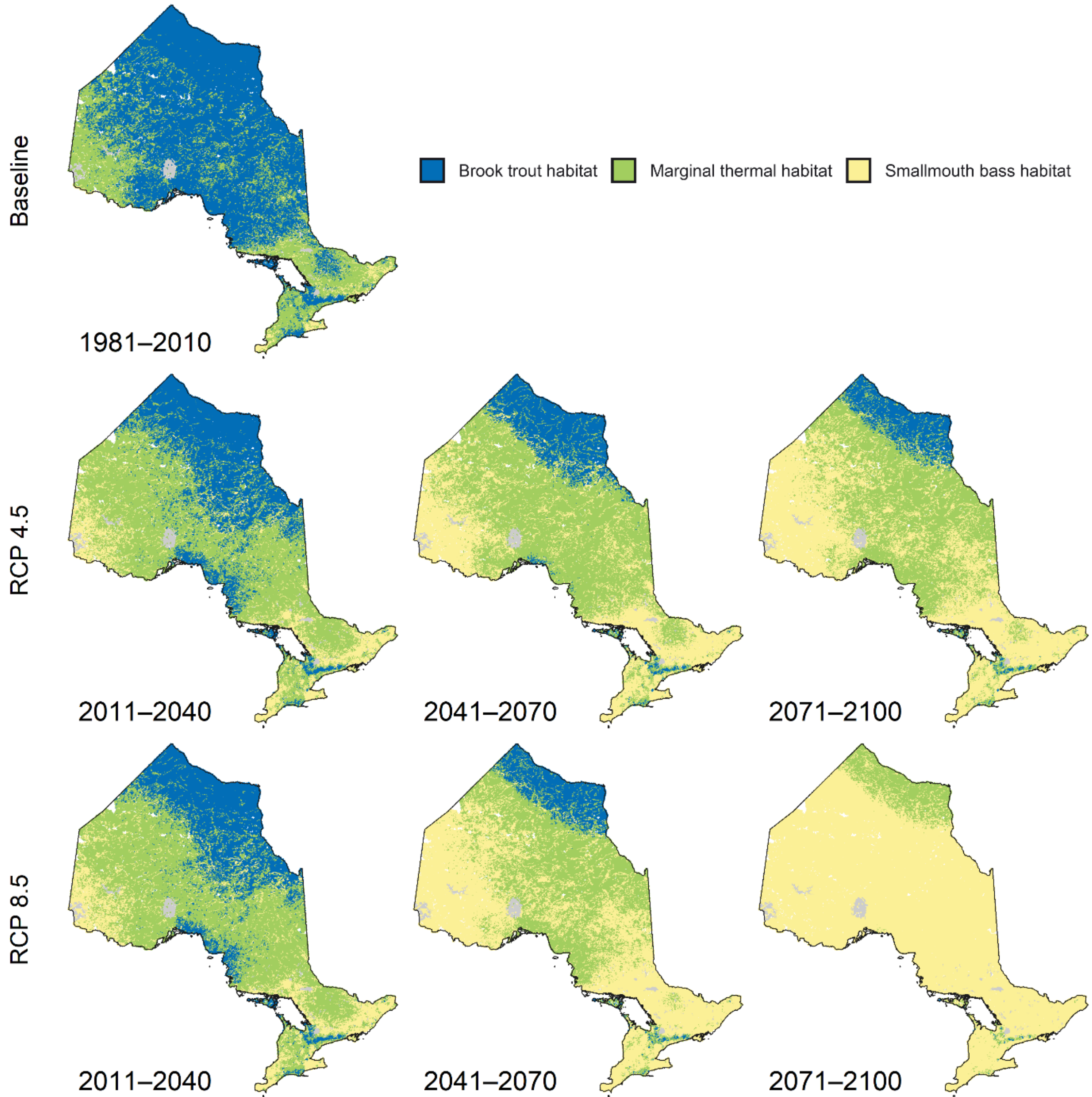

Figure 10. Projected thermal suitability of Ontario streams for brook trout and smallmouth bass under two representative concentration pathway (RCP) scenarios representing intermediate (RCP 4.5) and high (RCP 8.5) future greenhouse gas emissions. Temperatures <18.5 °C represented brook trout habitat, while temperatures >21.0 °C defined smallmouth bass habitat. Streams between 18.5 °C and 21.0 °C were classified as marginally suitable habitat for both species.

The performance of our final, optimized, temperature models (1.1–2.2 °C) compares favourably with the results of previous regional modelling studies that report predictive errors between 2–3 °C (e.g., Wehrly et al. 2009). Further, performance of the small streams (1.8 °C) and large river (1.1 °C) models for the OSD & HBL approached levels usually reserved for more complex spatial statistical network methods (e.g., Detenbeck et al. 2016, Isaak et al. 2017). Models fit using this approach often report predictive errors between 1.1 °C and 1.5 °C, but require much more data than was available in our data set. Overall, our models provide reliable predictions of July mean stream temperatures based on a small number of key variables, and represent a significant step forward in our understanding of stream temperatures across Ontario.

Given our modelling approach, the influence of all covariates matched expectations and theory. Higher air temperatures and larger drainage areas were associated with warmer temperatures, while higher baseflows and greater proportions of treed land cover were associated with colder streams. Surprisingly, including distance weighted covariates provided limited improvements in predictive performance despite a strong theoretical basis. However, when mapped, predictions from weighted models appeared to better reproduce expected longitudinal and spatial patterns in stream temperature. In most cases, the optimal weighting scheme approximated the optimal unweighted summary scale. For example, the optimal weighting scheme for treed land cover in the MWP model represents a narrow riparian buffer extending many kilometres upstream. This weighting scheme clearly approximates the upstream channel — the summary scale selected in the optimal unweighted model. Ultimately, further study is needed to determine if the benefits of distance weighting outweigh the added complexity and increased computational demands.

Several factors likely combined to limit the predictive performance of our temperature models. First, because the temperature data set was assembled from multiple sources, temperature monitoring sites were not randomly distributed on the landscape. As a result, there are gaps in spatial coverage — particularly in the north. Data is limited in regions that cannot be accessed by road and information is particularly lacking for many large northern rivers. Overall, there is a tendency to monitor larger streams (>50 km^2), leading to mismatches between the distribution of stream sizes on the landscape and represented in our data set. Small headwater streams are more challenging to model because of their among stream heterogeneity (Seelbach et al. 2011). Incorporating more data from headwater streams should improve predictive performance.

Given the heterogeneity and variability present in small streams, it is unsurprising that the OSD & HBL large river model was the top performing model. The low spatial resolution of the stream network (30 x 30 m) may be insufficient to fully differentiate landscape heterogeneity in smaller streams, making it difficult to explain variability in stream temperature. Errors in the position of the stream or its catchment will also propagate to the model when calculating distance weights and summarizing landscape characteristics. These errors are more consequential at small scales because fewer grid cells are contributing information to the model. As a result, access to higher resolution (e.g., lidar-derived) base data is likely required to improve model performance.

A lack of data describing the level of riparian shading provided by the different vegetation types composing the treed land cover class may also have contributed to model error. Future work could incorporate more accurate shading measures or include estimates of topographic shading (e.g., by stream banks or valley walls). Given the central importance of solar radiation to stream heat budgets, more accurately assessing the amount of solar radiation reaching the stream may substantially improve model performance. Similarly, model performance will likely be improved by including more accurate measures of groundwater flow. Although we used baseflow index as a proxy for groundwater input, it is based on coarse geological data that does not capture more complex features and interactions such as hyporheic exchange, fracture flow faults, and aquifer fed springs. Nevertheless, stream temperatures have been observed to be highly variable at the reach scale (Arscott et al. 2001, Ebersole et al. 2007, Moore et al. 2007) and, as such, any large-scale model will have inherent error driven by localized processes occurring at scales below the resolution of the available base data.

Temperature predictions

A robust understanding of stream temperature, and more broadly thermal regime, is crucial for effective management in aquatic ecosystems. Our temperature models produced accurate July mean stream temperature predictions for a 30-year period between 1981 and 2010. Headwater streams were usually predicted to be colder than larger mainstem rivers, consistent with theory and broad spatial patterns often found in lotic systems. There were clear relationships between climatic gradients, geological landforms, landscape characteristics, and predicted temperatures.

Using a novel probability-based method, we identified the thermal regime of every reach across Ontario. The probability-based approach allowed us to capture temporal variability over the 30-year baseline period and robustly classify thermal regimes. Classifying thermal regimes provides a better understanding of longitudinal and regional patterns in thermal habitat (e.g., for fishes). Cold, cold-cool, and cool thermal regimes currently dominate in Ontario, while warmer thermal regimes (cool-warm and warm) are largely confined to southeastern and southwestern Ontario. In northern Ontario, cool-warm and warm thermal regimes typically occur at lake outlets. This spatial thematic classification is a useful tool that can guide biologists unfamiliar with an area of interest.

Climate change projections

Climate change will present new realities and significant challenges for resource managers. As a result, a static perspective may no longer be appropriate for managing aquatic ecosystems. This view is supported by Milly et al. (2008) who suggested that “stationarity is dead”. Thompson et al. (2021) suggested that three management strategies exist under climate change: (1) resist changes while attempting to maintain existing ecosystems, (2) accept change when it cannot be resisted or when it is socially acceptable, and (3) direct change towards desirable ecosystem outcomes. The extent and rapidity of climate change may leave options 2 or 3 as the only viable strategies. As such, resource managers need sound projections to guide long-term planning, management, and the implementation of climate adaption strategies.

In contrast to previous efforts, our projections provide a local (reach) and broadscale (Ontario) understanding of future changes in stream temperature, thermal regimes, and thermal habitat availability for fishes under climate change. Previous projections for Ontario mainly focused on larger scales, such as quaternary watersheds (Chu et al. 2005, 2008), due to a paucity of stream temperature data. Our projections suggest that stream temperatures will increase substantially across Ontario over the coming century. These increases will be similar under both RCP 4.5 and RCP 8.5 during the 2030s before diverging over subsequent periods as failure to curb emissions leads to more rapid warming under RCP 8.5.

Cool, cool-warm, and warm thermal regimes will dominate by the 2080s in both scenarios, with coldwater habitat largely confined to northern streams near Hudson Bay and the headwaters of Lake Ontario tributaries along the Oak Ridges Moraine. Suitable thermal habitat for brook trout will persist as disconnected fragments, creating isolated populations at risk of local extirpations (Fagan 2002, Fausch et al. 2009, Isaak et al. 2015). In the near term, large rivers are projected to warm rapidly. As a result, cold tributaries will become increasingly important as thermal refugia for fishes. Nevertheless, streams will become increasingly suitable for smallmouth bass over the coming century. Although commonly associated with lakes in Ontario, smallmouth bass are also well suited to flowing waters (Scott and Crossman 1973). Indeed, smallmouth bass originated in the United States where flowing waters represented their primary habitats before deglaciation (Kitchell et al. 1977, Borden and Krebs 2009). Across the Great Lakes, warm rivers and estuaries provide considerable spawning and rearing habitat to smallmouth bass relative to colder inland lake or river environments (Jones and Parna 2024). Climate change may allow southern species to move north as warmer summer temperatures and shorter winters alter the conditions that historically shaped the distribution of northern fishes (Shuter et al. 2012).

Consistent with previous climate change modelling efforts, there are potential limitations in our approach. Our projections do not account for changes in hydrology or landscape characteristics, yet climate change and anthropogenic pressure will undoubtedly alter these attributes. Climate change is projected to increase precipitation frequency and intensity in many areas, with evaporation also increasing as temperatures rise (Mortsch et al. 2000). As a result, warming will require proportionally more precipitation to maintain current hydrologic conditions. Changes in flow are known to alter stream temperature, and reduced discharge is associated with warming due to reduction in thermal capacity (Caissie 2006). Groundwater temperatures within 100 m of the surface are usually 1–2 °C colder than the mean annual air temperature, suggesting that we should expect increased groundwater temperatures as air temperatures rise (Freeze and Cherry 1979). As such, the modelled relationships between baseflow and stream temperature may not hold true into the future. Similarly, climate change and future development will alter treed land cover, but our projections assume current levels of riparian vegetation will remain constant into the future. Future work could project temporal changes in hydrology and land cover to improve the accuracy of stream temperature projections under climate change.

Interpreting and using predictions

The predictions and thermal regime classifications produced in this research are not substitutes for empirical data. At the same time, a single year of data is insufficient to discard the modelling results. Stream temperatures are sensitive to climatic and hydrologic variation, such as whether a summer was cool and wet or warm and dry. Indeed, Jones and Schmidt (2018) found that July mean stream temperature variation averaged 3.5 °C, ranging between 1.2 and 7.6 °C, among 78 streams in Ontario. This finding means that, on average, July mean stream temperature may vary 3.5 °C from one year to the next. As a result, a stream classified as cold or cold-cool might occasionally reach temperatures exceeding 21.5 °C (i.e., the threshold for the warmwater class). We present class membership probabilities, in addition to July mean temperature predictions, at each reach to provide users with an understanding of expected interannual variation. A higher membership probability suggests lower interannual variation. For example, a reach with a 90% probability of being cold should have a July mean stream temperature exceeding 18.5 °C only 10% of the time (i.e., one in every ten years). Several years of data measuring temperatures above 18.5 °C could indicate modelling (e.g., incorrect predictions) or measurement (e.g., incorrect installation of the sensor) error. Generally, smaller groundwater-fed streams are the most stable, while mid-sized rivers exhibit more variation because they integrate heterogenous landscapes. Thermal regimes can be complex and challenging to interpret, and we refer readers to Jones and Schmidt (2019) for a detailed overview of stream temperature classification and interpretation.

Several caveats apply when using the stream temperature predictions. First, these models were developed from relatively coarse spatial data. As such, predictions represent average conditions over an entire stream reach and will not capture fine-scale heterogeneity driven by features such as deep pools, shallow riffles, or groundwater upwellings. Second, predictions in urban areas must be interpreted with caution. Urban streams were excluded during model development, and our model likely fails to capture important warming processes in these streams such as run-off from impervious surfaces. Third, predictions downstream of lakes, reservoirs, or dams should also be interpreted cautiously. Stream temperatures are often elevated immediately downstream from a lake outlet. This warming effect attenuates gradually and may continue for several kilometres before reaching equilibrium with the surrounding landscape. As a result, reaches flagged as lake influenced may have temperatures or thermal regimes that differ from the provided predictions (Figure 11). Nearly 48% of reaches (186,000 kilometres of stream) are lake influenced, including 178,750 kilometres of stream classified as cold, cold-cool, or cool. Although we did not estimate lake-adjusted temperatures in lake influenced reaches, we do provide lake surface temperature estimates for every lake outlet using a model developed by Bachmann et al. (2018; Appendix 2). Users can reasonably assume that the actual stream temperature falls somewhere between the provided lake outlet and stream temperature predictions. The temperature difference between the lake outlet and stream depends on many factors. For example, the processes driving stream temperature approximate the processes driving lake temperature as drainage size increases. As a result, larger rivers typically have temperatures similar to lakes. To aid interpretation, the AEC provides an estimated level of lake influence in each stream reach. Ongoing research is attempting to quantify lake influence on stream temperatures to allow explicit incorporation of lake influence in stream temperature modelling.

Further research is needed to understand how thermal classes relate to fish presence/absence and fish community compositions. Fishes have well defined thermal preferences due to the role temperature plays in regulating a range of biochemical, physiological, and life history processes. However, fishes can inhabit a range of temperatures — including temperatures several degrees warmer than their preferred temperature. Tolerable levels of temperature elevation depend on factors such as duration of exposure, availability of food resources, and the ability to find cooler water (i.e., thermal refugia). Although fish will seek thermal refugia during the summer months, temperatures are not limiting for the remaining months of the year. Therefore, fishes can move freely throughout the stream network or into lakes. In the winter, fishes may move into warmer water to find overwintering habitat. In watersheds without barriers (e.g., dams), fish can exploit spatial variation in stream temperatures to maximize fitness. The complexity of stream thermal regimes has led to a common misconception that coldwater fishes will only ever be observed in coldwater streams. In fact, coolwater streams may support the highest biomass and production of trout (Lyons et al. 2009). Temperature is only one of many determinants of habitat suitability for fishes, and temperature alone may not directly predict presence/absence of a given species.

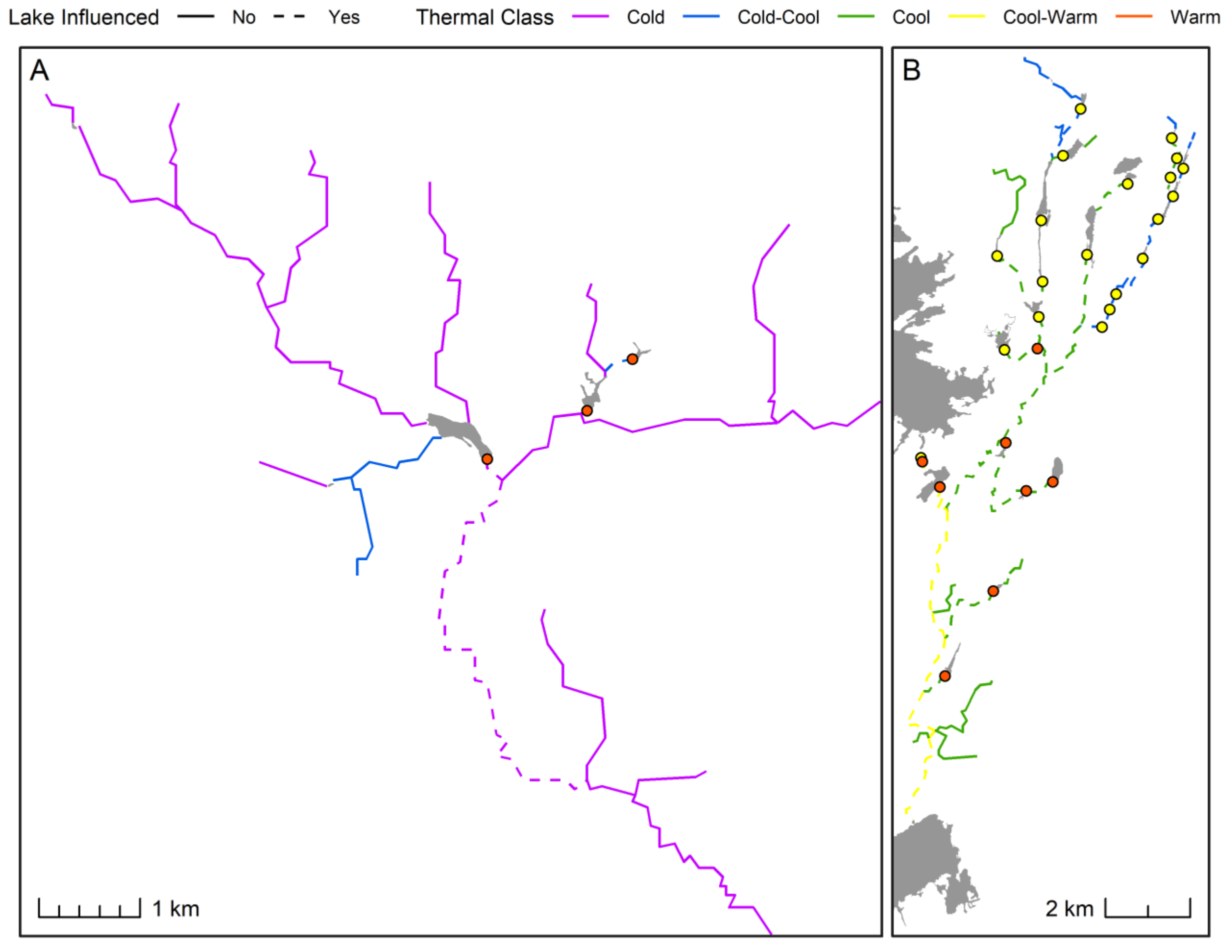

Figure 11. Examples of lake influence in (A) a small headwater stream and (B) a larger tributary. The lake surface temperature at the outlet (coloured circles) is typically much warmer than the predicted stream temperature. Predicted stream temperatures below lake outlets (dashed line) should be interpreted with caution and likely fall somewhere between the predicted lake outlet and stream temperatures. In some cases, waterbodies will be too small to exert an influence on streams downstream of the outlet (e.g., the pond in upper left of panel A). In other cases, many sequential lakes lead to a continuous zone of lake influence (panel B).

Conclusions

For the first time, we can predict and map the distribution of stream temperatures and thermal regimes across Ontario. Our results show that Ontario is currently dominated by cold, cold-cool, and cool thermal regimes, with considerable heterogeneity in temperature across the province. Climate change is projected to alter the existing thermal regime of many streams and result in a landscape dominated by cool, cool-warm, and warm streams depending on the time period and scenario. These models, temperature predictions, and climate change projections represent the best products available given existing data and resources. Predictions and projections produced by these models can be applied to a range of management problems such as mapping thermally suitable habitat, identifying thermal refugia, stratifying streams in research and monitoring, and prioritizing conservation efforts.

Future improvements of these models are conditional on improvements in the base data and an increase in the quantity, quality, and distribution of stream temperature data. Higher resolution (e.g., lidar-derived) hydrology data will improve the positional accuracy of the stream network and limit error when calculating landscape summary metrics. Similarly, access to more accurate and higher resolution landscape data (e.g., land cover and geology) could improve our ability to model the underlying processes influencing stream temperature. Also recommended is a robust stream temperature monitoring network to provide baseline data and assess the progression of climate change. Current monitoring is ad-hoc and information management is lacking. Collating data from disparate sources every 5 to 10 years to revisit temperature models and assess status and trends is inefficient and time consuming, particularly when most tasks could be automated. Any future monitoring network must be developed strategically to represent the varied stream types and thermal regimes across Ontario. Additional temperature data is needed from smaller systems where shading and groundwater inputs strongly influence stream temperature. The Aquatic Ecosystem Classification and results of the present study could be used as a base to identify stream types of interest and ensure monitoring is representative.

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Appendix 1. Classifying thermal regimes

Algorithm 1 below illustrates the thermal class assignment process. Transitional thermal classes identify streams that fall between the core classes (e.g., cold and cool or cool and warm). These streams may flip from one class to another depending on if the summer is cool and dry or warm and wet (Figure 1.1). For example, a cool-warm stream may be cool during a colder summer but warm during a hot summer. In contrast, a stream assigned to one of the three core classes (i.e., cold, cool, and warm) might only flip to another class in an extreme year. Thermal classes were assigned based on 30 years of stream temperature predictions between 1981 and 2010. We use the predictions to calculate class membership probability and account for interannual variation. Class membership probabilities are provided for each stream reach in Ontario. For management applications, it may be prudent and precautionary to group the transitional thermal classes with neighbouring classes. For example, if the aim is to identify thermal refugia for coldwater species, the cold and cold-cool classes could be grouped.

ALGORITHM 1: CLASSIFY THERMAL REGIME

Input: A vector T of temperatures in °C with length > 1

Output: $Cold$, $ColdCool$, $Cool$, $CoolWarm$, or $Warm$ depending on the distribution of T

Let $mean(x) = \frac{1}{n}\sum_{i=1}^{n} x_i$

Let $stdev(x) = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$

Let $pnorm(X,\ x) = \frac{1}{2}\left[1 + \text{erf}\,(\frac{x-\bar{x}}{\sigma\sqrt{2}})\right]$

Let $\bar{x} = mean(T)$
Let $\sigma = stdev(T)$

Let $p_{cold} = pnorm(T, 18.5)$
Let $p_{cool} = 1 - pnorm(T, 21.5) - p_{cold}$
Let $p_{warm} = 1 - \ p_{cold} - p_{cool}$

if $p_{cold} > 0.8$ **then**
    return $Cold$
else if $p_{cool} > 0.8$ **then**
    return $Cool$
else if $p_{warm} > 0.8$ **then**
    return $Warm$
else if $p_{cold} + p_{cool} > 0.8$ **and** $p_{warm} + P_{cool} > 0.8$ **then**
    return $Cool$
else if $p_{cold} + p_{cool} > 0.8$ **then**
    return $ColdCool$
else if $p_{warm} + p_{cool} > 0.8$ **then**
    return $CoolWarm$
end

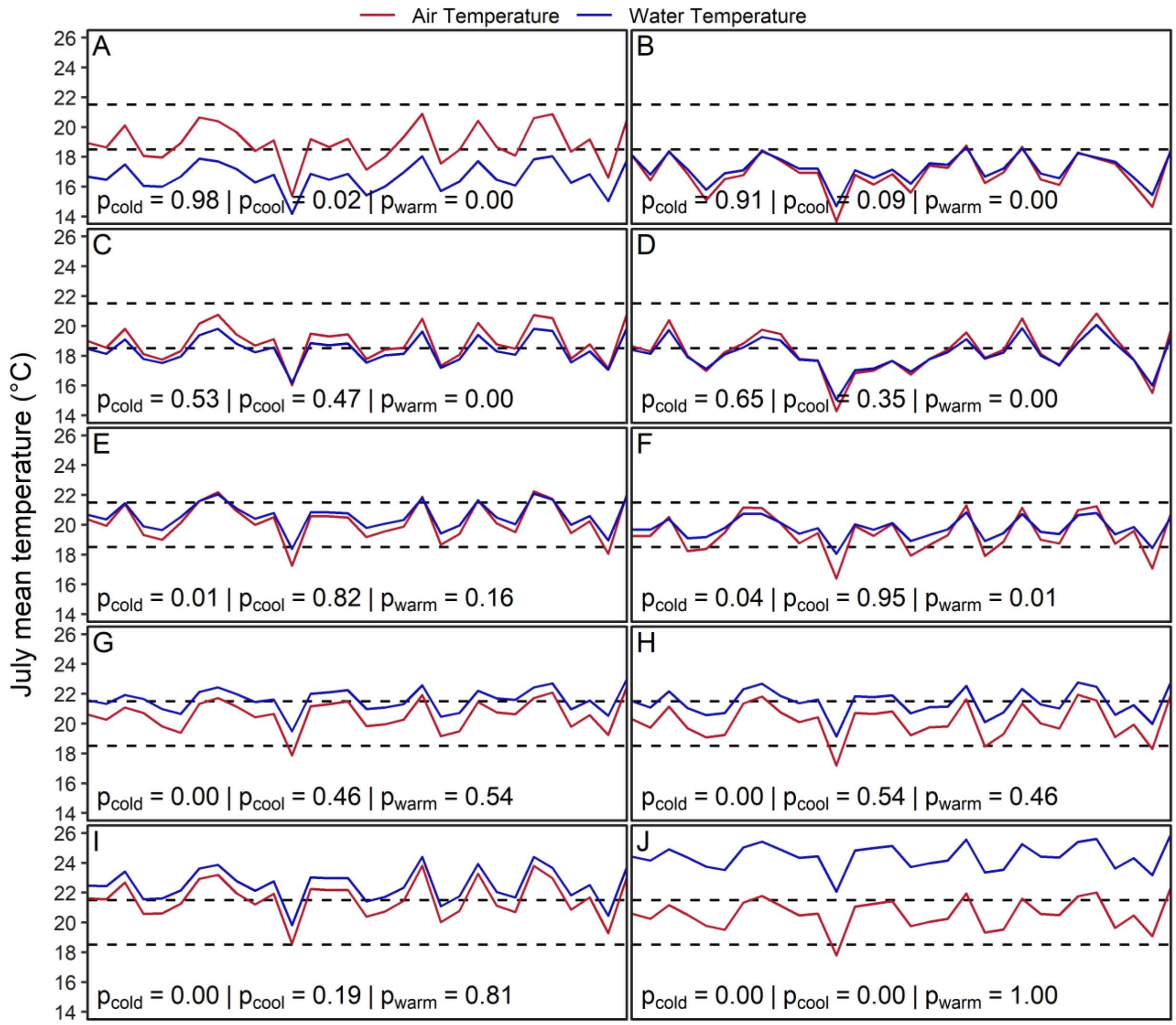

Figure 1.1. Example July mean temperature time series for cold (A,B), cold-cool (C,D), cool (E,F), cool-warm (G,H), and warm (I, J) thermal regimes predicted for a 30 year period between 1981 and 2010 in Ontario. The probability of membership for the core thermal classes (cold (p_{cold}), cool (p_{cool}), and warm (p_{warm})) over the 30-year period is shown for each time series.

Appendix 2. Predicting lake surface temperatures

Lakes and reservoirs can increase stream temperatures by inundating downstream reaches with warm epilimnetic water (Jones 2010, Leach et al. 2023). Due to a lack of data and an incomplete understanding of the magnitude and downstream extent of lake effects on stream temperature we did not attempt to incorporate lake influence into our stream temperature models or adjust stream temperature predictions in lake influenced reaches. Nevertheless, it is important for end users to have an estimate of water temperature at the lake outlet to allow interpretation of the unadjusted stream temperature predictions. As such, we used a model developed by Bachmann et al. (2018) to predict lake surface temperatures across Ontario. Developed with data from 750 Canadian lakes, this model was originally intended to predict daily mean temperatures at 1 m in depth and is not Ontario specific. However, to our knowledge, it is the only model available to predict July mean, and not maximum, lake surface temperatures. When validated using a small data set (78 lakes; 320 July temperature records) extracted from our temperature database, we found a root mean squared error (RMSE) of 1.48 °C. This result compares favourably with the RMSE of 2.2 °C reported in the original paper. However, the model has a large negative bias and tends to overpredict for lakes smaller than 1000 ha (Figure A2.1).

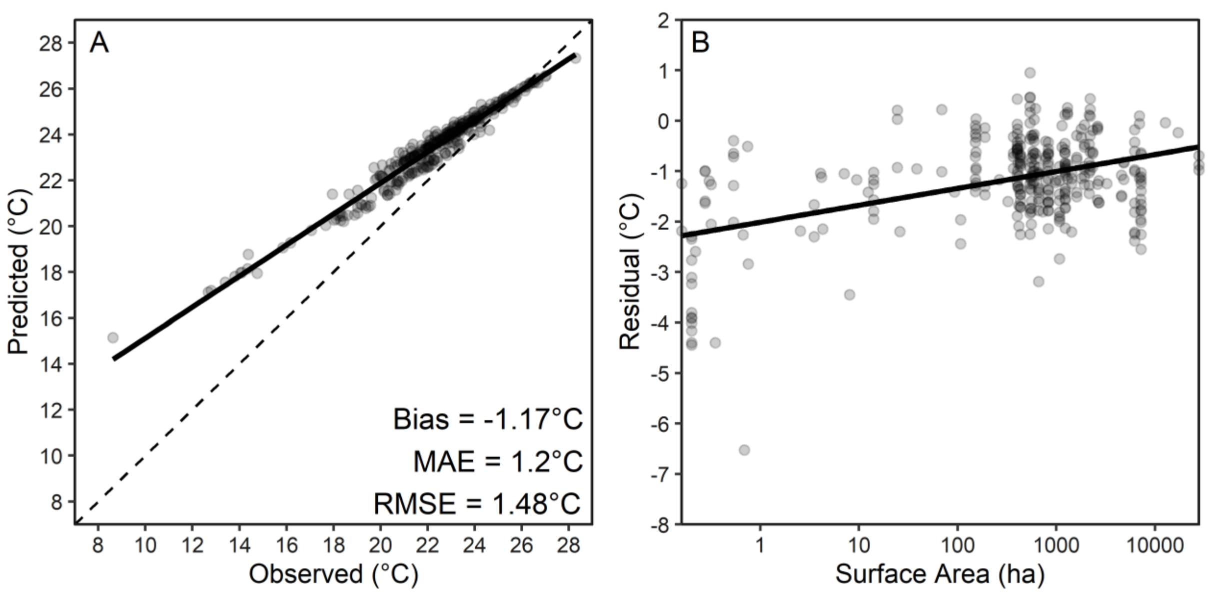

Figure A2.1. Predictive performance of the Bachmann et al. (2018) July lake surface temperature model (A) and variation in predictive performance with lake surface area (B) when applied to a small validation data set from Ontario lakes (78 lakes; 320 July temperature records).

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