Thermal habitat of flowing waters in Ontario: Prediction and classification

Technical Report TR-43

Science and Research Branch

Ministry of Natural Resources and Forestry

Ontario

Science and Research Technical Report TR-43

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2021

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Cite this report as:

Jones, N.E., B.J. Schmidt, I.A. Sutton and K. Ghunowa. 2021. Thermal habitat of flowing waters in Ontario: Prediction and classification. Ontario Ministry of Natural Resources and Forestry, Science and Research Branch, Peterborough, ON. Science and Research Technical Report TR-43. 23 p.

Summary

Water temperature is an important ecological resource that defines thermal habitat for aquatic biota, which determines species distribution and abundance; nutrient and ice dynamics; and the metabolic activity, growth, timing of migration, and spawning events of fishes. As such, a robust understanding of the thermal regime of rivers and streams is needed for effective resource management and environmental impact assessment.

Most aquatic field sampling focuses on one location for one summer within a complex stream network. This approach can lead to inaccurate estimates of thermal regime using point-in-time sampling. Further issues stem from not knowing how far upstream or downstream from the sampling point the measurement applies.

We developed temperature models to predict average July average stream temperatures (i.e., average July temperatures averaged over multiple years) for streams in the Mixedwood Plains and large rivers across Ontario. We implemented a novel statistical approach using 30 years of climate data to classify streams into five thermal classes. We focused specifically on July because peak annual temperatures are typically observed across the province in this month, which may limit the availability of suitable thermal habitat for many aquatic species.

After extensive quality control and scrutiny of the data and an in-depth analysis of the influence of stream size, we modelled July average stream temperatures using linear mixed effect modelling (LMM). Two final models were developed: one for small streams <700 km^2 and another for larger streams. While large streams were predicted across the province, only small streams were predicted in the Mixedwood Plains Ecozone. Data in northern Ontario is lacking, but efforts are underway to remedy this gap. Cross-validation suggested reasonable model accuracy and a small positive bias for large streams. It also indicated that the small stream model had lower predictive accuracy (root mean square error (RMSE)=2.05 °C) than the large rivers model (RMSE=1.03 °C) and both models had a slight positive bias.

The predictions made here are not a substitute for empirical data. The maps can provide guidance on what to expect for a stream reach. They may also help guide sampling efforts in the field, particularly in areas with uncertainty/lack of knowledge. The predictions for stream temperature do not provide baseline conditions for making comparisons to data from field-based monitoring programs. The predictions are based on 30-year averages, which differs from a given year that could be dry and hot or wet and cold. Stream temperature predictions below lake outlets should be interpreted with caution, as lakes will often be substantially warmer than a stream not draining a lake given the same landscape characteristics.

Sommaire

Habitat thermique des eaux vives en Ontario : prévision et classification

La température de l’eau est une importante ressource écologique qui définit l’habitat thermique du biote aquatique, lequel détermine la répartition et l’abondance des espèces, la dynamique des éléments nutritifs et de la glace, et l’activité métabolique, la croissance, le calendrier des migrations et les événements du frai des poissons. Il est donc nécessaire de bien comprendre le régime thermique des rivières et des cours d’eau pour gérer les ressources et évaluer l’impact environnemental efficacement.

La plupart des prélèvements d’échantillons effectués en milieu aquatique sur le terrain sont axés sur un seul emplacement au cours d’un été donné dans un réseau de cours d’eau complexe. Cette approche peut produire des estimations inexactes du régime thermique à l’aide d’un prélèvement d’échantillons ponctuel. D’autres problèmes découlent du fait de ne pas savoir jusqu’à quelle distance en amont ou en aval du point de prélèvement d’échantillons la mesure s’applique.

Nous avons élaboré des modèles de température pour prédire les températures moyennes des cours d’eau en juillet (c.-à-d. les températures moyennes en juillet calculées sur plusieurs années) pour des cours d’eau des plaines à forêts mixtes et des grandes rivières de l’Ontario. Nous avons mis en œuvre une nouvelle approche statistique en utilisant trente années de données climatiques pour classer les cours d’eau en cinq classes thermiques. Nous nous sommes concentrés en particulier sur juillet parce que les températures maximales annuelles sont généralement observées au cours de ce mois dans toute la province, ce qui peut limiter la disponibilité d’un habitat thermique adéquat pour de nombreuses espèces aquatiques.

Suite à un contrôle de la qualité approfondi, à un examen minutieux des données et à une analyse approfondie de l’influence de la taille des cours d’eau, nous avons modélisé les températures moyennes des cours d’eau en juillet à l’aide de la modélisation linéaire à effets mixtes (MLM). Deux modèles finaux ont été élaborés : un pour les petits cours d’eau < 700 km^2 et un autre pour les grands cours d’eau. Bien que de grands cours d’eau aient fait l’objet de prévisions dans toute la province, seuls de petits cours d’eau ont fait l’objet de prévisions dans l’écozone des plaines à forêts mixtes. Les données dans le nord de l’Ontario font défaut, mais des efforts sont en cours pour combler cette lacune. La validation croisée porte à croire que le modèle est raisonnablement précis et qu’il y a un léger biais positif pour les grands cours d’eau. Elle a également indiqué que le modèle des petits cours d’eau avait une valeur prédictive (écart moyen quadratique (EMQ) = 2,05 °C) inférieure à celle du modèle des grands cours d’eau (EMQ = 1,03 °C) et que les deux modèles présentaient un léger biais positif.

Les prédictions faites ici ne remplacent pas les données empiriques. Les cartes peuvent fournir des indications sur ce à quoi il faut s’attendre pour un tronçon donné d’un cours d’eau. Elles peuvent également contribuer à guider les efforts de prélèvement d’échantillons sur le terrain, en particulier dans les zones pour lesquelles il existe une incertitude ou un manque de connaissances. Les prévisions concernant la température des cours d’eau ne fournissent pas les conditions de référence qui permettent de faire des comparaisons avec les données obtenues des programmes de surveillance sur le terrain. Les prévisions sont fondées sur des moyennes sur trente ans qui diffèrent des conditions d’une année donnée qui pourrait être sèche et chaude ou humide et froide. Les prévisions concernant la température des cours d’eau sous les décharges des lacs doivent être interprétées avec prudence car les lacs sont souvent nettement plus chauds qu’un cours d’eau qui ne draine pas un lac pour des caractéristiques du paysage identiques.

Acknowledgements

We thank the many biologists and summer students who sampled streams and provided temperature data. We greatly appreciate funding from the Ministry of Natural Resources and Forestry’s Integrated Monitoring Framework for Rivers and Streams and for the air temperature grids supplied by Dan McKenney, Natural Resources Canada.

Contents

Introduction

Water temperature is an important ecological resource that defines thermal habitat for aquatic biota (Magnuson et al. 1979). The temperature of water has been described as a master abiotic variable for fishes (Brett 1971, Hannah and Garner 2015) that defines species distribution and abundance, nutrient and ice dynamics, and the metabolic activity, growth, timing of migration, and spawning events of fishes (Caissie 2006; Prowse 2001a, b). More broadly, the thermal regime is important to the ecological integrity of aquatic ecosystems. In turn, it is necessary to have a robust understanding of the thermal regime of rivers and streams for effective resource management and environmental impact assessment.

The assessment of thermal regime is often based on limited data collected for a single year (e.g., data for July and August collected using a stream temperature logger). However, this snap-shot approach is vulnerable to natural inter-annual variability, where some years may have hot dry summers while others are cool and wet. In Ontario, Jones and Schmidt (2018) found the mean annual variability of July average stream temperatures for 78 streams was 3.5 °C with a range of 6.3 °C. As a result, thermal classification approaches that depend on point-in-time sampling (e.g., Stoneman and Jones 1996, Chu et al. 2009) are vulnerable to misclassification. Indeed, accurate calculation of thermal regime metrics (e.g., July average stream temperature) may require 12 or more years of data. Alternative approaches where stream fishes are sampled, and the thermal classification is inferred from known thermal preferences and tolerances (Wichert and Lin 1996) may be more reliable. However, these approaches are labour intensive and costly, and still fail to provide an understanding of temporal variability in the thermal regime.

Another key issue with common approaches to thermal regime classification is knowing how to extrapolate temperature upstream or downstream from a sampling station. Confidence quickly decreases as distance from the sampling point increases, particularly in small streams that rapidly increase in size and integrate increasingly heterogenous landscapes. The combined uncertainty in the temporal and spatial variation in temperature indicates a low confidence in estimating stream temperature and classifying thermal regime across space and time. Furthermore, this uncertainty shows that we have a poor understanding of the available thermal habitat. In turn, modelling and predicting stream temperatures is needed to better understand interannual variability at a finer spatial scale. Such a spatial layer would provide an enormous advantage over current practices and enhance our understanding of the availability of critically important thermal habitats across Ontario.

We developed temperature models to predict July average stream temperatures for streams in the Mixedwood Plains and large rivers across Ontario. We then implemented a novel statistical approach using 30 years of climate data to classify streams into five thermal classes. The thermal classifications were used to develop an understanding of thermal habitat across Ontario. We focused specifically on July because that is when peak annual temperatures typically occur across the province. Summer also represents the period of the year when the availability of suitable thermal habitat may be limited, particularly for coldwater species.

Methods

Stream temperature

Stream temperature data were sourced from several provincial government partners including the Surface Water Monitoring Centre, regional and district offices, and externally from, for example, conservation authorities and federal agencies (e.g., Fisheries and Oceans Canada). These records were aggregated with a long-term monitoring data set collected by the Ministry of Natural Resources and Forestry's River and Stream Ecology Lab to form an initial network of temperature monitoring stations. These monitoring stations were incorporated into the provincial Aquatic Ecosystem Classification (AEC; Jones and Schmidt 2017) framework by manually assigning stations to a reach using notes generated during data acquisition. Stations that could not be reliably associated to a reach (e.g., due to incorrect or missing coordinates) were excluded from the data set at this stage.

The stream temperature data underwent a thorough quality control/quality assurance process prior to modelling. First, time series were plotted for July of each year and visually inspected for data quality. For each station, time series were compared within and across years to find and exclude periods of invalid data (e.g., sensor out-of-water, buried, or malfunctioning; Figure 1). July mean stream temperatures were then calculated for all years with data available for >80% of July. This threshold was established to capture the full range of variability in July temperatures. In some instances, partner agencies provided data directly as July mean values. Where possible, these means were quality controlled in a similar manner to the raw time series data (e.g., by comparing monthly means to minimums/maximums to infer evidence of burial or drying). Ultimately, confidence was lower in values provided directly as means so, during further aggregation and cleaning, time series derived values were selected preferentially.

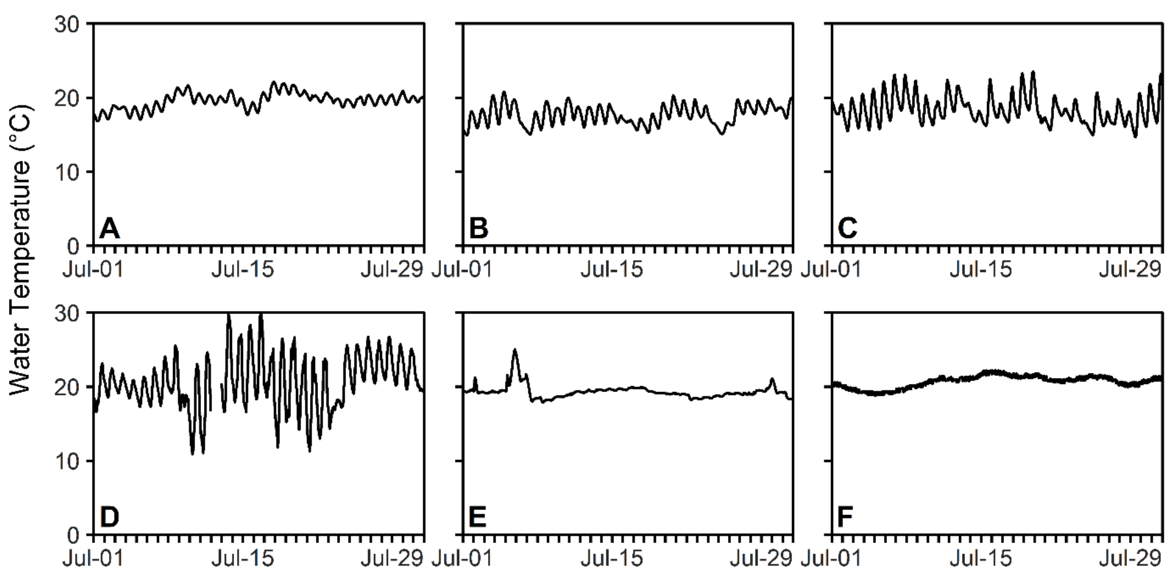

Figure 1. Examples of July average water temperature time series for rivers and streams at sample plots across Ontario, Canada. The examples in the top row (A-C) show time series with a range of valid daily water temperature values. Examples in the bottom row show suspected out-of-water (D), buried (E), and malfunctioning (F) sensors.

Following initial quality control, sampling stations influenced by lakes, reservoirs, and urbanized areas (>10% catchment urbanization) were excluded from the data set because these factors can drastically alter landscape-scale process. Ontario has numerous lakes and reservoirs. As a warning, streams flowing out of these waterbodies (outlets) are likely warmer than predicted, particularly the small streams. For the AEC we estimate a "zone of influence" downstream from every lake as a continuous attenuation function based on the size of the stream (width). For small streams the lake influence attenuates quickly (<1 km), whereas it may take several kilometres for larger streams. We are conducting further research to develop a more complex model to quantify this effect.

July mean temperatures were then plotted against July mean air temperatures to assess the stability of the air-water temperature relationship. Years with inconsistent relationships were excluded from the data set (Figure 2). Stream temperature data from the remaining stations was then aggregated at reach scale. For reaches containing multiple stations, the station with the longest record was kept intact with any remaining, non-overlapping, data from other stations used to fill gaps or extend the time series. Following aggregation, air-water temperature relationships were re-evaluated and any years with inconsistent patterns (e.g., due to reach-scale heterogeneity) were removed from the data set.

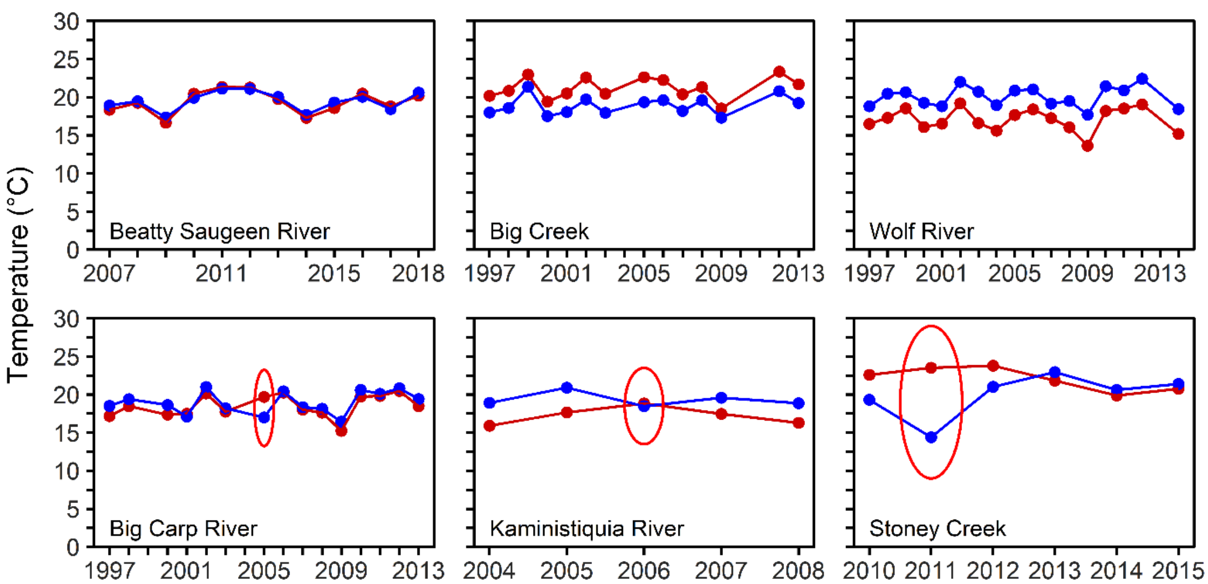

Figure 2. Examples of good (top row) and bad (bottom row) relationships between July average air (red) and water (blue) temperature for rivers in Ontario, Canada. July average water and air temperatures are similar for the Beatty Saugeen River, whereas air temperature is typically warmer than water temperature for Big Creek and vice-versa for the Wolf River. Problem data points diverging from the overall pattern are identified in the bottom row {red circles} for the Big Carp, Kaministiquia, and Stoney rivers.

The final stage of data cleaning was the removal of spatially autocorrelated reaches. Reaches within the same AEC neighbourhood were assumed to be autocorrelated and, like the removal of duplicate records, the reach with the longest continuous record was retained for modelling. In brief, neighbourhoods are adjacent flow-connected reaches on the same stream. Their boundaries are defined by confluence symmetry rules (stream size as upstream catchment area; see Jones and Schmidt 2017). The data quality control/quality assurance process substantially reduced the data available for modelling, resulting in a data set of 2,145 years of data for 782 monitoring stations and 721 AEC reaches (Figure 3). A figure summarizing the data cleaning stages is provided in Appendix A.

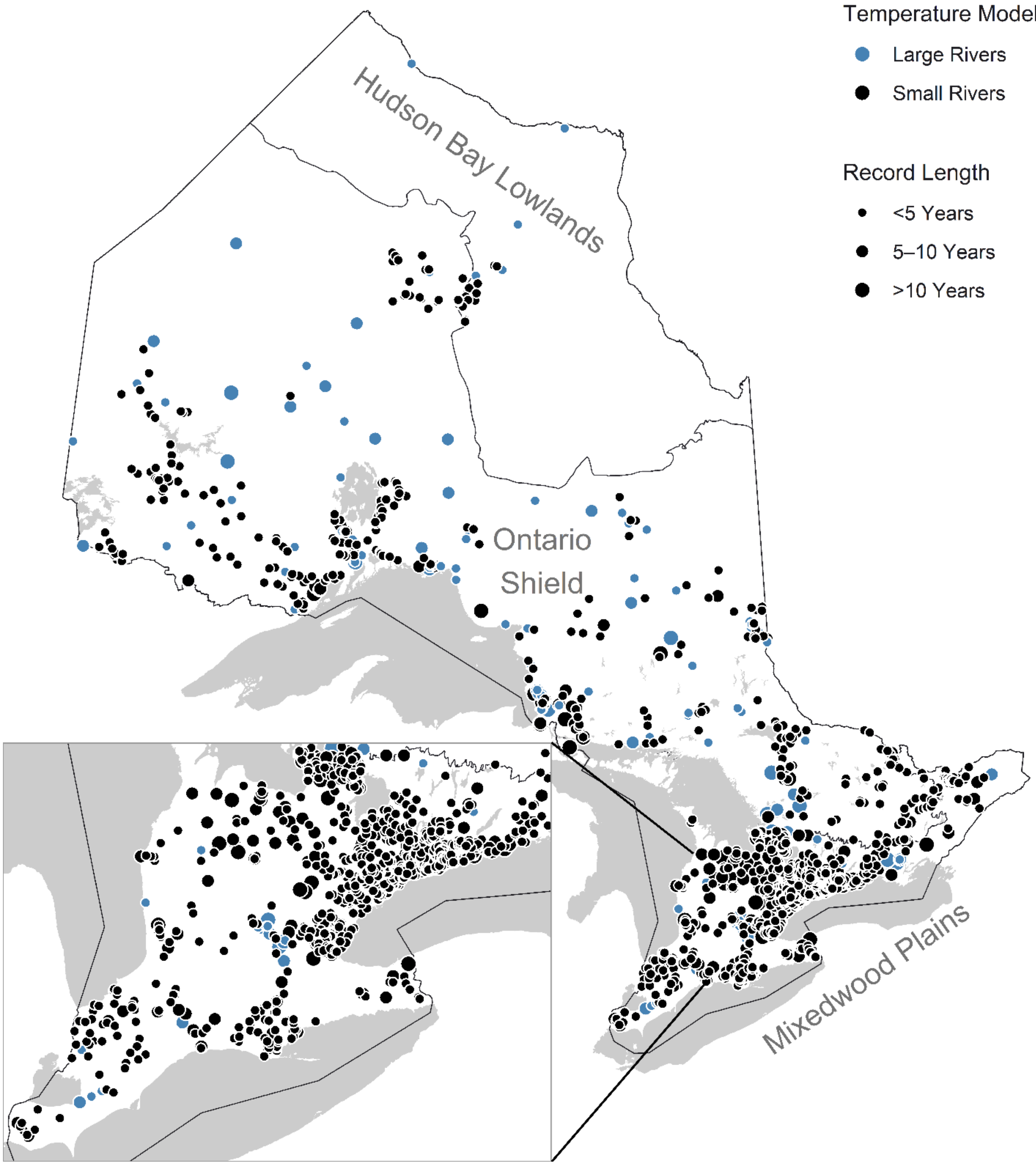

Figure 3. Stream temperature monitoring sites in Ontario. Blue (large river) and black (small river) points are stations used to develop the predictive temperature models. Grey lines are ecoregion boundaries. For details, see the Modelling Approach section and Appendix A.

Air temperature

July minimum and maximum air temperature grids, with a resolution of approximately two arc-seconds obtained from Natural Resources Canada, were used to calculate July average air temperatures for each year between 1980 and 2018. Due to the mismatch in spatial resolution, air temperatures were assigned to each reach using the air temperature grid cell intersecting the reach centroid. All processing was completed using ArcGIS Pro 2.4.0 (ESRI, Redlands, CA).

Landscape processes

The AEC framework provides an inventory of landscape characteristics representing geology, topography, and land cover summarized at four spatial scales for each reach: reach catchment area (RCA), upstream catchment area (UCA), reach channel (RCh), and upstream channel (UCh) (Figure 4). A set of candidate variables believed to influence stream temperature were extracted from this data set for use as independent variables in modelling. Variables were selected based on the results of previous studies (see Appendix B), exploratory data analyses, and professional judgment. Table 1 provides an overview of the candidate variables and their expected effect on July average stream temperatures. For complete list of available landscape characteristics and their calculation, see Jones and Schmidt (2017).

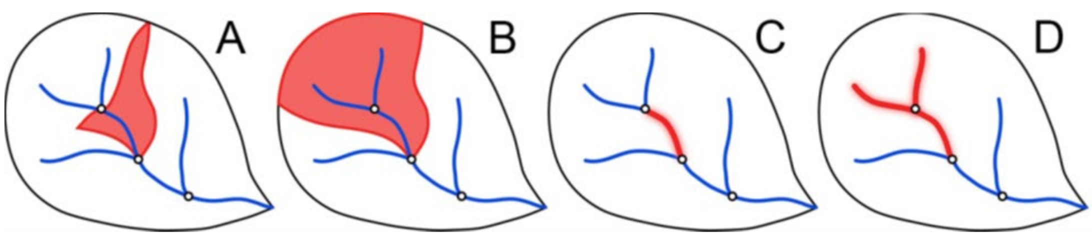

Figure 4. The four spatial scales used to summarize stream reach landscape processes in Ontario's Aquatic Ecosystem Classification: A) reach contributing area, B) upstream catchment area, C) reach channel, and D) upstream channel.

Table 1. Landscape characteristics considered in July average stream temperature (T_w) models. (NA=not applicable)

Variable	Description[1]	Unit	Scale(s)	Influence on T_w
T_a	July average air temperature	°C	RCh	↑
Aspect	Watershed southern aspect; surrogate for incoming solar radiation	%	UCA	↑
Area	Upstream drainage area; surrogate measure of channel size	km^2	UCA	↑
BFI	Baseflow index; a measure of groundwater potential	NA	UCA, RCA	↓
Overburden	Mean overburden thickness; the depth of permeable materials	m	UCA, RCA	↓
Elevation	Mean channel elevation	m	RCh	↓
Slope	Mean channel slope	°	RCh	↓
TWI	Topographic wetness index; measures topographic controls on runoff generating processes	NA	UCA, RCA	↑
Lakes	Lake area	%	UCA, RCA	↑
Wetland[2]	Wetland area	%	UCh, RCh	↑
Treed[2]	Treed area	%	UCh, RCh	↓

[1] Detailed descriptions and methods are provided by Jones and Schmidt (2017).
[2] These variables are aggregated; see Appendix C for details.

Modelling approach

Data exploration and model breakpoints

Jones and Schmidt (2016) found that smaller watersheds often have homogenous landscapes because their small drainages often encompass a single landscape type. This homogeneity contrasts with conditions in larger watersheds that integrate a heterogenous landscape composed of many types. This increased heterogeneity results in reduced variability and a common averaged condition among larger watersheds. As a result, for progressively larger drainages the zonal statistics of landscape characteristics will begin to approach the mean value of the entire data set (Figure 5).

Air temperatures were observed to become increasingly correlated to stream temperatures at larger spatial scales (Figure 6), reflecting the homogenization of landscape characteristics for larger watersheds. This correlation poses a potential challenge for modelling as the increasing

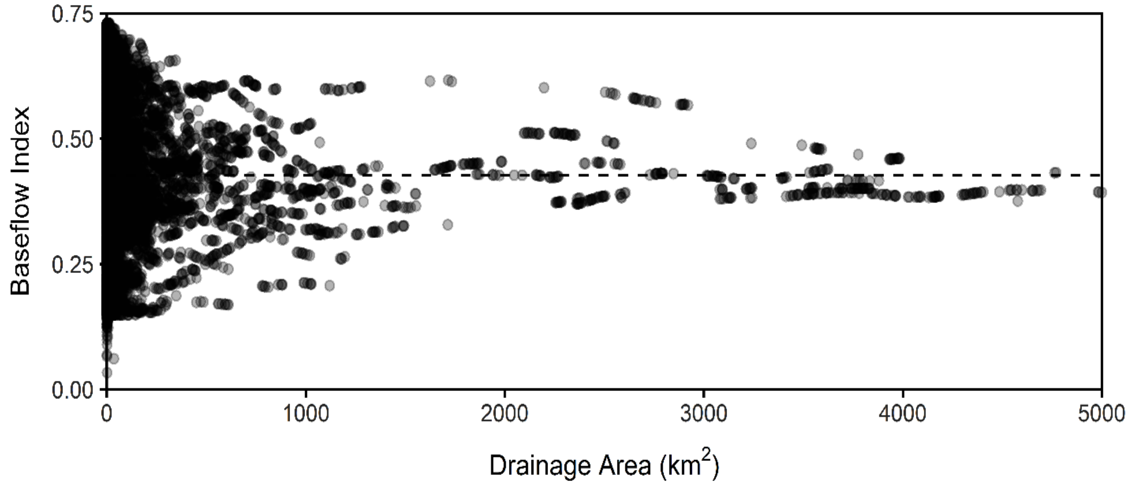

Figure 5. Relationship between drainage area and baseflow index for the Mixedwood Plains, an example of landscape homogenization with increasing drainage size. The horizontal dashed line represents the grand mean of baseflow index for the Mixedwood Plains.

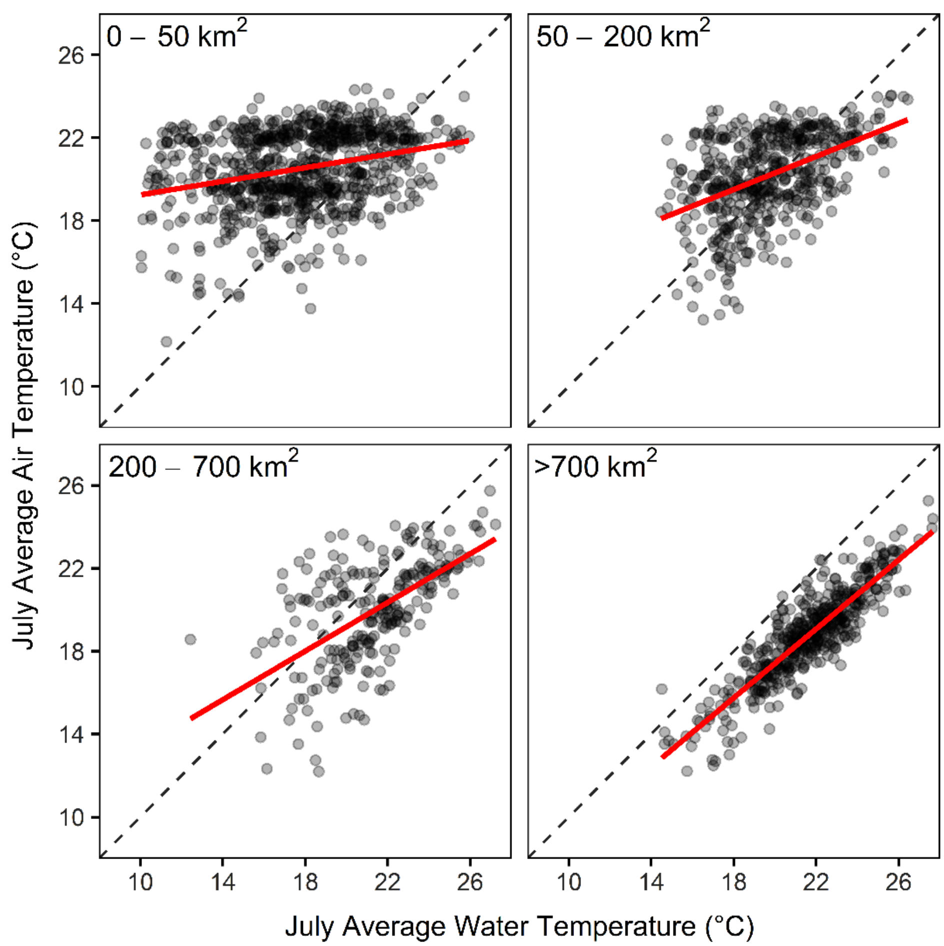

Figure 6. Correlation between July average air and water temperatures in relation to drainage size for the Mixedwood Plains. The diagonal dashed line is a 1:1 reference line while the solid red line represents a linear relationship between air and water temperatures fit using ordinary least squares regression.

dominance of air temperature for large watersheds may lead to lost understanding of the drivers of stream temperature at smaller spatial scales. In addition, uncertainty may be overestimated for larger systems as the model struggles to partition variance. To mitigate these issues, the data set was divided into small streams and large rivers based on catchment size. These data sets were then modelled separately. Reaches with drainage areas larger than 700 km^2 were assigned to the large river model, with the remaining reaches assigned to the small streams model. This split was determined by examining the correlation between water and air temperatures at various spatial scales and by evaluating plots of the landscape predictors as a function of drainage area to identify drainage sizes at which values approached the grand mean across all reaches.

Small streams were additionally subdivided into models for each ecozone (Mixedwood Plains, Ontario Shield, and Hudson Bay Lowlands) due to differences in geology and climate (Crins et al. 2009). Reaches that crossed ecozone boundaries were assigned to the ecozone that contained >50% of their drainage area. Due to the lack of accurate geology data and a paucity of stream temperature data for the small streams of the Ontario Shield and Hudson Bay Lowlands, a small stream model was developed for the Mixedwood Plains only. The large river model applies to all of Ontario.

Model development and performance

July average stream temperatures were modelled using linear mixed effect modelling (LMM). A key benefit of the LMM approach is the ability to take advantage of the hierarchical structure of the sampling design. Multiple years of data from the same reach can be explicitly grouped, accounting for within reach variability and the non-independence of repeated sampling at reach scale. This explicit handling of non-independence allows correct inference of the effects of modelling covariates (e.g., landscape processes) on stream temperature. The LMMs were fit using the lme4 package (Bates et al. 2015) in R (R Core Team 2020).

Model development began with a model considering only the main effect of air temperature:

$$T_w \sim T_a + (1|Reach)$$

where T_w is July average stream temperature, T_a is July average air temperature and *1|Reach* represents reach random effects. Reach random effects were fit as random intercepts, which constrains the overall relationship with T_w to a singular slope while allowing intercepts to vary for individual reaches. Landscape covariates were then added through a stepwise procedure in descending order of the predicted importance of their influence on stream temperature. We also considered the interactions between several of the landscape covariates. For example, the effects of riparian vegetation (i.e., shading) are expected to decrease as drainage size increases (e.g., as streams become larger/wider). Landscape covariates (and interactions) that improved performance (i.e., increased prediction accuracy) were retained as predictors in the final model.

Due to the small size of the modelling data sets, model performance was assessed using 10-fold cross-validation. The data sets were subdivided into 10 folds stratified by reach, with a roughly equal number of reaches partitioned across each fold. Although folds are commonly stratified to contain an equal number of observations, stratification by reach (i.e., all years of data for one reach are contained within a single fold) was necessary to prevent data leakage and ensure that cross-validation was completed using novel data.

Model performance was assessed using root mean square error (RMSE) and bias:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

$$bias = \bar{P} - \bar{O}$$

where P_i and O_i are the predicted and observed values of T_w for the ith measurement, n is the total number of observations, and $\bar{P}$ and $\bar{O}$ are the mean predicted and observed values of T_w. RMSE provides a measure of model accuracy while bias measures the consistency of estimates (i.e., the tendency of the model to over-/underpredict). Performance measures were calculated for the full model (i.e., the model fit to the full data set) and the cross-validation folds. To assess performance on novel data, the RMSE and bias for the cross-validation folds were averaged.

Temperature prediction and thermal classification

Predictive models typically provide a single temperature prediction for a stream reach based on the average temperature over a given period (e.g., a 30-year climate normal). This approach has the benefit of providing a single value that is easy to interpret, but at the cost of providing little information about inter-annual variability in stream temperature. Models that rely on point-in-time sampling (e.g., Stoneman and Jones 1996, Chu et al. 2009) ignore inter-annual variations in air temperature. A more robust approach to temperature prediction involves using multiple years of field data to generate probabilities for a given temperature (e.g., for a 10-year period, 2 years, or 20%, had temperatures above 18.5 °C). However, this approach requires >12 years of data to generate probabilities accurately (Jones and Schmidt 2018).

As an alternative, a model could be used to predict stream temperatures over multiple years. For example, 30 years of July average air temperature data could be used to predict 30 years of July average water temperatures. The predictions can be used to generate a distribution and probabilities for different temperature thresholds (e.g., the probability of July average water temperatures exceeding 18.5 °C over a 30-year period). We applied this approach using the best model at each spatial scale to predict July average temperatures from 1980 to 2010. Using 30 years of climate data provides a means to capture temporal variability in stream temperatures and leads to enhanced understanding of the consistency and availability of the thermal habitat through time.

Thermal classification of streams is challenging, as stream temperatures can vary greatly in time and space. A stream’s thermal class is typically described as cool, cold, or warm water based on the dominant stream biota present during the summer (Table 2). These classes are often based on the thermal tolerance of fishes and the temperature thresholds for different classes can vary based on the region (e.g., states, provinces, equatorial, tropical, temperate) and the fish species present (e.g., trout, bass, catfishes). For example, smallmouth bass (*Micropterus dolomieu*) are classified as a warm-water species in Ontario but are considered a cool-water species in southern states.

Table 2. Examples of temperature thresholds (°C) used to define stream thermal classifications. (NA=not applicable)

Study	Thermal class				
	Cold	Cold transition	Cool	Warm transition	Warm
Wehrly et al. 2003*	<19.0	NA	19.0–22.0	NA	>22.0
Lyons et al. 2009	<17.5	17.5–19.5	NA	19.5–21.0	>21.0
McKenna et al. 2010	<18.0	18.0–21.0	NA	21.0–24.0	>24.0
Beauchene et al. 2014	<18.5	NA	18.4–22.3	NA	>22.3

* In addition to cool, cold, and warm, three temperature fluctuation categories were specified.

Thermal classes are meant to represent thermal habitat available for fishes, but this assumption is rarely satisfied in practice. Fishes can be found in a range of water temperatures due to the physiological and behavioural coping strategies that allow them to tolerate temperatures that are warmer or colder than ideal. Furthermore, groundwater inflows can provide patches of colder water (thermal refugia) that allow coldwater species to exist in streams that would be too warm otherwise. This leads to a misconception that coldwater fishes such as trout will only be observed in coldwater streams. In fact, cool-water streams support the highest production and biomass of trout (Lyons et al. 2009). In addition, warm-water species (e.g., bass and catfish) can often be found among coldwater fishes during the summer months. As noted by Lyons et al. (2009), no diagnostic species uniquely represents coldwater streams and overlap with warm- and cool-water assemblages is often significant. Similarly, Beauchene et al. (2014) observed a narrow 3.4 °C temperature range between cold- and warm-water thresholds. This region was designated as a cool water transition zone with potential for both cold- and warm-water species and a lack of species uniquely associated with this thermal range.

Ideally, separation of species would be clear among the three thermal classes (Figure 7A), but this is rarely the case as species will have overlapping temperature preferences that result in little clarity (Figure 7B). This overlap is apparent on a histogram of final temperature preferences for 88 fish species found in Ontario's flowing waters (Hasnain et al. 2013; Figure 7C). While some evidence exists of a division at 19.0 °C, support is minimal for an intermediary cool-water class often seen in other thermal classifications. Similarly, although Wherly et al. (2003) contend that two clear breaks in community temperature preferences are evident for stream fishes in Michigan, a singular break at about 19.0 °C is more plausible. Magnuson et al. (1997) noted a similar two-group distribution when plotting laboratory thermal preferences against temperature occupation measured in the field. They suggested that a skewed distribution between 20 and 35 °C provides evidence for cool- and warm-water groups despite considerable overlap. Magnuson et al. also suggested that some fishes will group by family with respect to temperature preference: e.g., centrarchids, ictalurids, and percichthyids (e.g., sunfish, catfish, bass) are a warm-water guild; percids and esocids (e.g., perch) form a cool-water guild; and salmonids (e.g., salmon/trout) constitute a cold-water guild. In contrast, cyprinids (minnows/carp) are more diverse with species distributed across all three guilds.

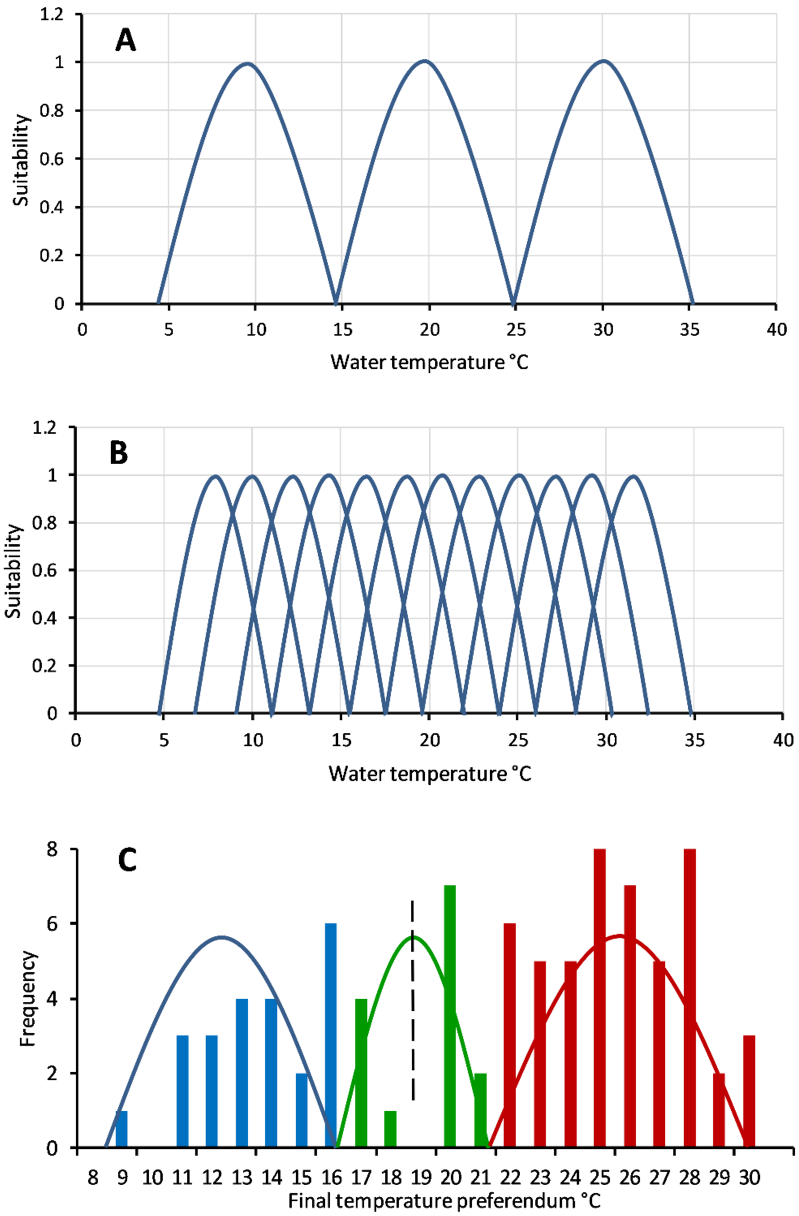

Figure 7. Ideal distribution of thermal preferences for fishes (A). In fact, many fishes with varying temperature preferences provide little indication of clear groupings (B). In Ontario, the final temperature preferenda for 88 fish species documented by Hasnain et al. (2013) provide little evidence for cold, cool, and warm-water thermal classes commonly used to characterize stream thermal regimes (C). The histogram bars and overlaid distributions are coloured to represent the cold (<19 °C), cool (19–22 °C), and warm (>22 °C) classes used by Wehrly et al. (2003). For thermal preferenda data, refer to Appendix D.

Given the general lack of species separation by thermal preference, thermal classes are largely constructs developed for management purposes and to aid in understanding. As a result, cold-, cool-, and warm-water classes and associated temperature thresholds are simplified conventions adopted by resource managers. The lack of clear groups may stem from (i) the scale of analysis, which is very broad and includes many species, and (ii) patterns of gradual longitudinal stream temperature change (Troia et al. 2016). In contrast, individual lakes are smaller in scale with fewer species and distinct thermal strata composed of epilimnion, metalimnion, and hypolimnion are evident in summer. In turn, each of these layers have representative fishes (Brandt et al. 1980).

More recently, authors have begun including additional classes such as the 4-class cold, cold transition, warm transition, and warm system applied in Michigan and Wisconsin (Lyons et al. 2009) or the 5-class system of cold, cold-cool, cool, cool-warm, and warm developed for Ontario streams (Chu et al. 2009). In New York, McKenna et al. (2010) used point-in-time temperature measurements to develop four thermal classes. At present, it is not clear whether the increasing complexity of thermal classifications better reflects reality or has any useful applications in a management context for flowing waters.

In the present study, we applied a 5-class approach to classify stream temperature predictions. This approach is consistent with the five classes of Chu et al. (2009); however, the classes were determined using different methods. The approach of Chu et al. uses a single measurement of daily maximum air temperature (≥24 °C) and water temperature at 1600 hours between July 1 and September 7, which is plotted on a nomogram to approximate the thermal classification of a site. In contrast, our approach uses 30 years of July average air temperature combined with landscape covariates to predict 30 July average stream temperatures and their statistical distribution (i.e., mean, standard deviation) for each reach.

We applied class thresholds (cold: <18.5 °C, cool: 18.5–21.5 °C and warm: >21.5 °C) that were similar to those used by others to these distributions to calculate a z-score for each thermal class based on the mean and standard deviation of stream temperature predictions derived from 30 July average stream temperature predictions for each reach. A probability threshold of 0.8 was used to determine class membership. For example, a reach with a 17 °C July average temperature and a standard deviation of 0.8 °C over the 30 years would have a probability of 0.97 of belonging to the cold class. As a result, this reach would be classified as cold-water (Figure 8). A reach was assigned to a transitional class (cold-cool or cool-warm) when the membership probability did not exceed 0.8 for any of the three classes. In these cases, the combination of class probabilities exceeding 0.8 was used to assign the reach to a transitional class. For example, a reach with a 0.73 cold class probability and a 0.27 cool class probability is assigned to the cold-cool class because the combined cold and cool probabilities exceed 0.8. This five-class method explicitly incorporates uncertainty into the thermal classification scheme because class membership is based on probabilities. This approach should provide an improved understanding of thermal classification and more accurately represent the true inter-annual variability of the thermal regime.

Thermal habitat characterization

Stream temperature predictions and the five-class thermal classification framework were used to develop an understanding of thermal habitat in the Mixedwood Plains. As mentioned, this analysis was restricted to the Mixedwood Plains due to the lack of a model to predict stream temperatures and thermal classifications for reaches on the Ontario Shield and Hudson Bay Lowlands. To develop an understanding of available thermal habitat, the raw and classified temperature predictions from both temperature models (i.e., the large river and Mixedwood Plains small stream models) were combined. We then calculated the number of reaches and length of stream belonging to each of the five thermal classes. To better understand how thermal habitats are distributed from headwaters to outlet, we plotted the raw and classified stream temperature predictions as a function of Strahler order. This analysis has the potential to provide an understanding of rare thermal habitats with conservation interest.

Five classes

Temp °C	Cold <18.5	Cool 18.5-21.5	Warm >21.5	
15.0	1.00	0.00	0.00	
15.5	1.00	0.00	0.00	
16.0	1.00	0.00	0.00	
16.5	0.99	0.01	0.00	
17.0	0.97	0.03	0.00	
17.5	0.89	0.11	0.00	
18.0	0.73	0.27	0.00	
18.5	0.50	0.50	0.00	Cold-cool
19.0	0.27	0.73	0.00	
19.5	0.11	0.89	0.01	
20.0	0.03	0.94	0.03	
20.5	0.01	0.89	0.11	
21.0	0.00	0.73	0.27	
21.5	0.00	0.50	0.50	Cool-warm
22.0	0.00	0.27	0.73	
22.5	0.00	0.11	0.89	
23.0	0.00	0.03	0.97	
23.5	0.00	0.01	0.99	
24.0	0.00	0.00	1.00	
24.5	0.00	0.00	1.00	
25.0	0.00	0.00	1.00	

Figure 8. Overview of the five-class framework. Thermal class is determined by the probability of membership to a given base class (cold, cool, or warm). Class membership is achieved when the probability exceeds a threshold, in this case, p>0.8. The grey bands illustrate transitional temperature classes (cold-cool, cool-warm) where the probability of membership to cold, cool, or warm is low (e.g., p<0.8). The five-class method explicitly incorporates uncertainty because class is determined by the probability of class occupancy. For more details, see Jones and Schmidt (2019).

Results

Temperature models

The final model for large rivers had the form:

$$T_W \sim T_a + Treed\ (UCh) + (1|Reach)$$

This model explained 93.9% of the total variation in July average water temperature for large rivers (>700 km^2), with reach scale random effects accounting for 19.1% of the variation. Cross-validation suggested reasonable model accuracy (RMSE = 1.03°C) and a small positive bias (Table 3).

The final model for the small streams of the Mixedwood Plains had the form:

$$T_w \sim T_a + UCA + BFI\ (UCA) + Overdurden\ (RCA) + TWI\ (UCA) + Treed\ (UCh) + (1|Reach)$$

This model explained 95.7% of the total variation in July average stream temperature; however, much of the variation (41.4%) was accounted for by reach scale random effects. Cross-validation indicated that the small stream model had lower predictive accuracy (RMSE = 2.05 °C) than the large rivers model and a slightly larger, but still positive, bias (Table 3).

July average stream temperatures were characterized by a positive response to air temperature and a negative response to upstream channel riparian vegetation in both models (Table 4). The additional terms in the Mixedwood Plains small streams model indicated that drainage area and upstream catchment topographic wetness index were positively related to stream temperature while baseflow index and reach catchment overburden thickness had negative relationships. All terms for the Mixedwood Plains small stream model were significant, while the air temperature term was the only significant predictor for the large river model. However, an increase in model accuracy when riparian vegetation was included caused it to be retained in the final model.

Table 3. Model performance summary statistics for the predictive stream temperature models total number of reaches ($N_{Reaches}$) and years of data (N_{years}), marginal (R^2_m) and conditional (R^2_c) coefficient of determination, root mean square error (RMSE), and bias for the full model and 10-fold cross-validation (CV). Large rivers include all large rivers (>700 km^2) across Ontario. Small streams are just for drainages in the Mixedwood Plains Ecozone.

Model	$N_{Reaches}$	N_{Years}	R^2_m	R^2_c	RMSE	Bias	CV RMSE	CV bias
Large rivers	95	493	0.75	0.94	0.51	0.00	1.03	0.03
Small streams	424	1,237	0.54	0.96	0.54	0.00	2.05	0.15

Table 4. Parameter estimates for the predictive stream temperature models for large rivers and small streams in the Mixedwood Plains in Ontario: coefficient (ß), 95% confidence interval (CI), t-statistic (*t*), degrees-of-freedom (df) and p-value (*p*).

Model	Parameter	ß	CI	*t*	df	*p*
Large rivers	*Intercept*	4.17	3.35 – 4.98	10.06	397.27	<0.001
	T_a	0.92	0.88 – 0.96	46.35	415.34	<0.001
	Treed (UCh)	0.009	-0.02 – 0.02	1.60	84.38	0.11
Mixedwood Plains small rivers	*Intercept*	2.89	0.76 – 5.02	2.67	481.53	<0.01
	T_a	0.67	0.64 – 0.70	42.07	817.97	<0.001
	UCA	0.008	0.006 – 0.01	7.98	403.08	<0.001
	BFI (UCA)	-2.67	-4.09 – -1.25	-3.69	416.97	<0.001
	Overburden (RCA)	-0.02	-0.03 – -0.02	-6.91	408.66	<0.001
	TWI (UCA)	0.72	0.44 – 1.00	5.06	421.41	<0.001
	Treed (UCh)	-0.03	-0.05 – -0.02	-4.94	418.61	<0.001

Temperature prediction and thermal classification

Obvious spatial associations were evident between geologic and landscape characteristics and the predicted temperatures (Figure 9) and thermal classes (Figure 10). Geologic landforms

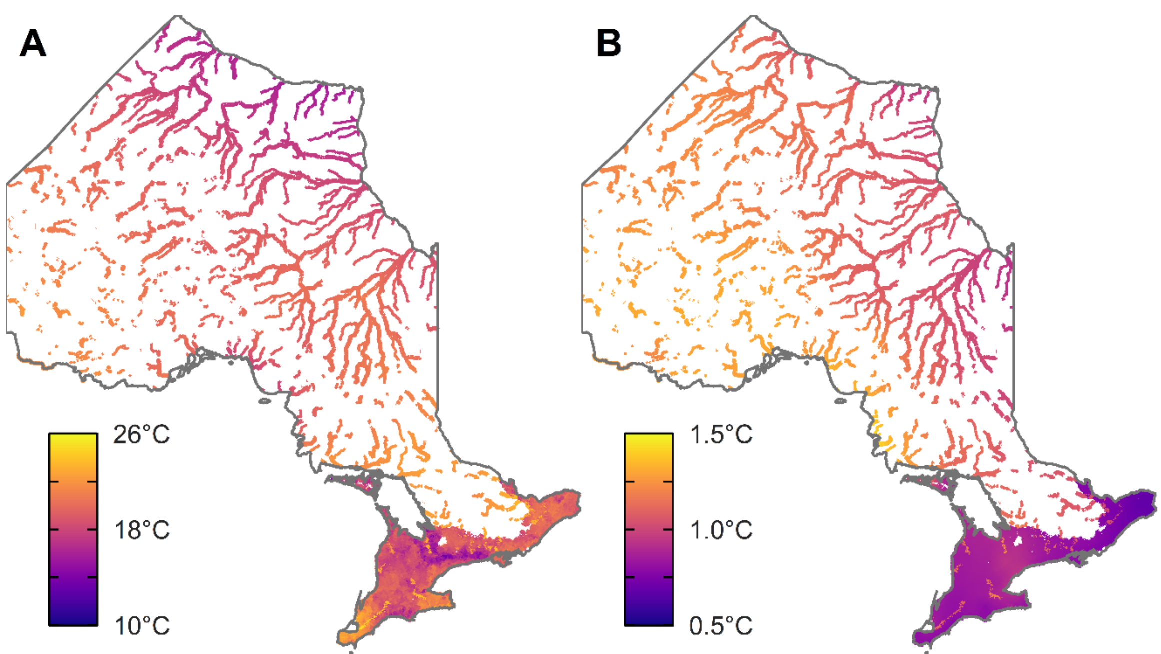

Figure 9. Spatial patterns in the mean (A) and standard deviation (B) of July average stream temperatures predicted for small streams in the Mixedwood Plains and large streams across Ontario using 30 years of climate data (1980–2010).

including the Oak Ridges Moraine, northern Niagara Escarpment, and Norfolk sand plain associated with increased groundwater supply due to highly permeable glacial deposits of sand and gravel and steep topographic gradients are predicted to be home to cold and cold-cool streams. Warm and cool-warm streams are frequently observed on the southwestern and southeastern clay plains, where low topographic relief and baseflow result in lower groundwater inputs while increasing warm surface run-off during summer storm events. In addition, clear gradients of decreasing temperature were evident along a south-north gradient and east of Lake Superior as a function of climatic air temperature gradients and inland lake effects.

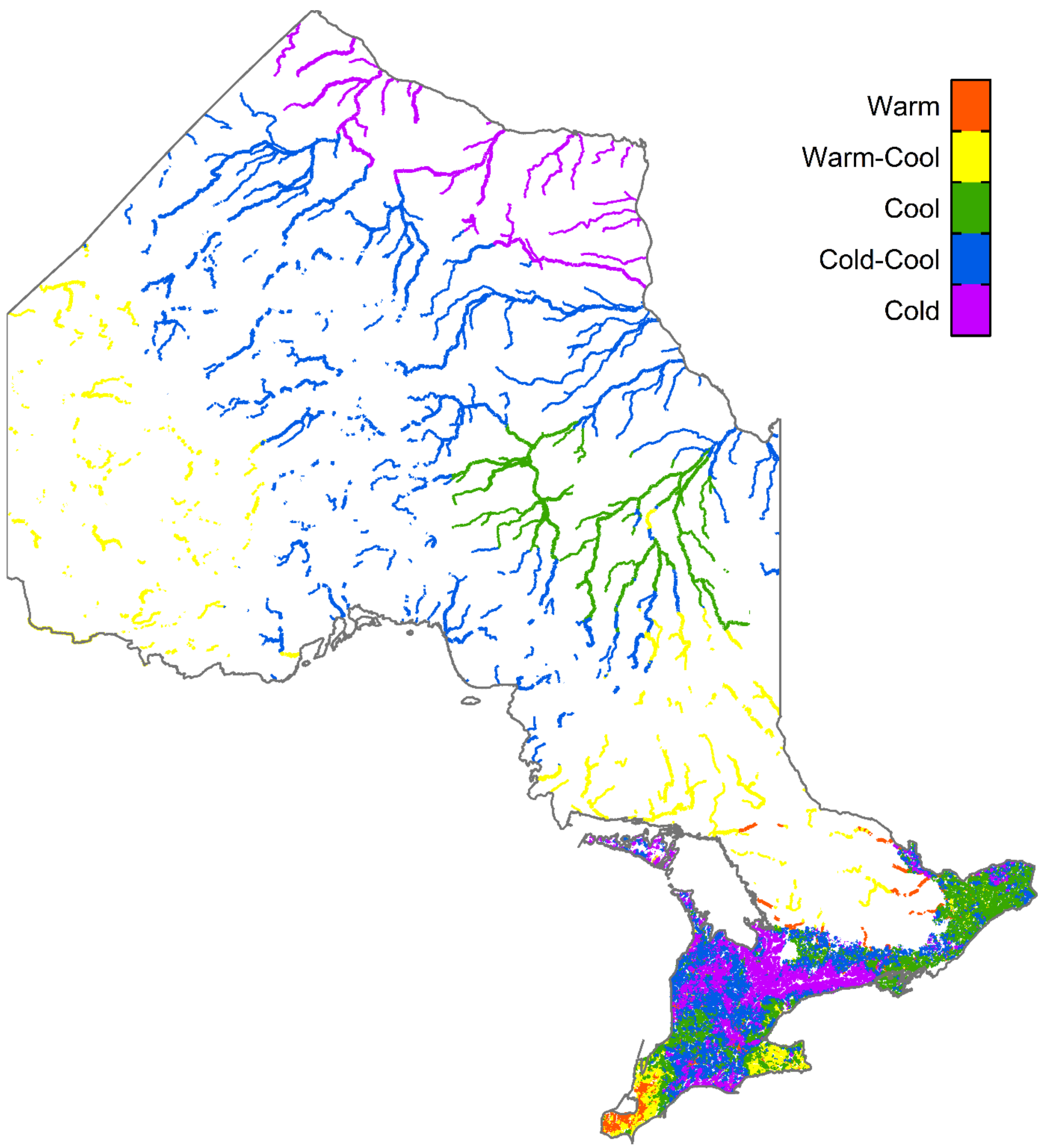

Figure 10. Thermal classification of July average stream temperatures in Ontario predicted using 30 years of climate data (1980–2010). Predictions are shown for the large river model and the model for small Mixedwood Plains streams.

Thermal habitat

Cool and cold-cool transition habitats are abundant in the Mixedwood Plains, representing 63% of all reaches and 62% of stream length (Table 5). Coldwater habitat is also abundant, while warm-water habitat is the most limited. Coldwater habitat becomes increasingly rare for larger rivers, with no coldwater habitat observed beyond Strahler order 5 (Figure 11). This reflects the primary importance of air temperature at larger spatial scales.

Table 5. Distribution of thermal habitat by thermal class in the Mixedwood Plains Ecozone.

Attribute	Thermal class				
	Cold	**Cold-cool**	**Cool**	**Cool-warm**	**Warm**
Stream reaches (#)	6,020	9,155	10,500	2,146	3,334
Stream length (km)	7,820	12,264	17,230	4,046	6,084

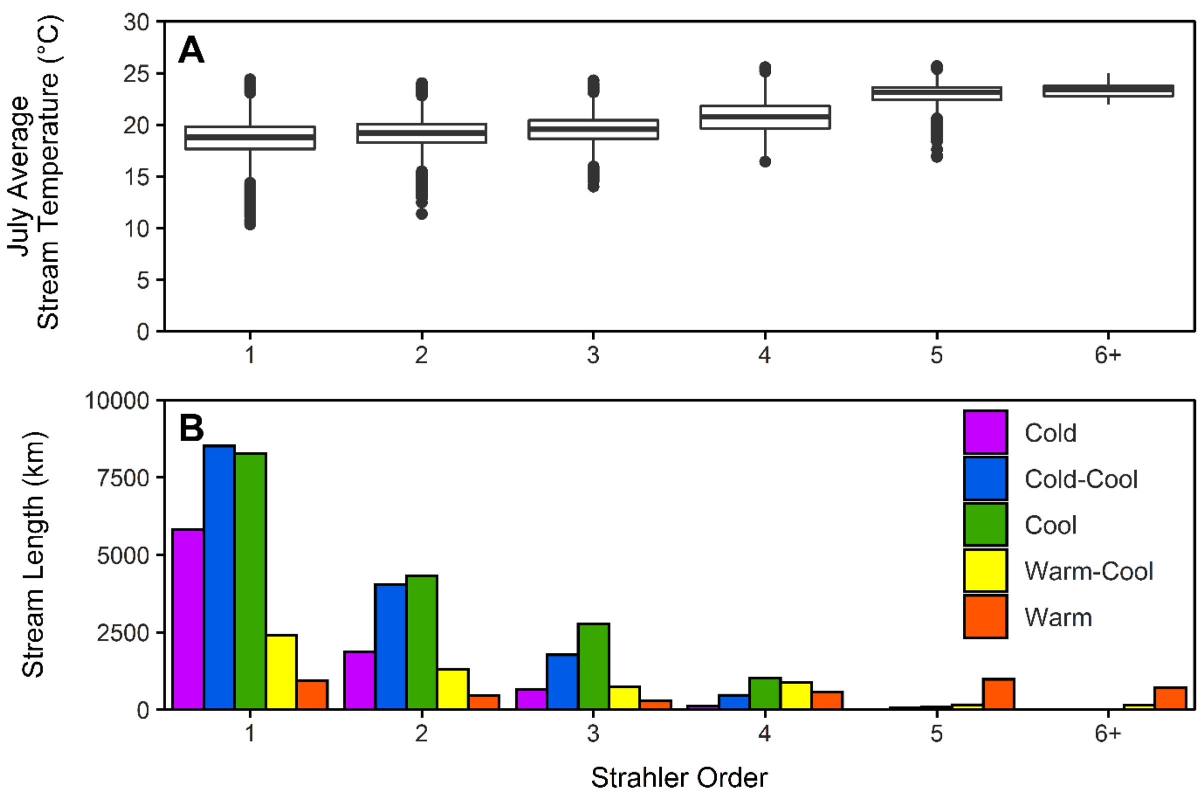

Figure 11. Distribution of predicted July average stream temperatures for the 30-year climate normal (A) and stream length by thermal class (B) for each Strahler order in the Mixedwood Plains Ecozone.

Discussion

Temperature models

The final predictive stream temperature models for the small streams of the Mixedwood Plains and large rivers of Ontario are consistent with our understanding of the multi-scale processes influencing stream temperature. Small streams were found to be influenced by a combination of reach (model variables: air temperature, mean overburden thickness) and catchment (model variables: drainage area, baseflow, topographic wetness index, riparian vegetation) conditions. Larger rivers were less sensitive to local processes and thus are primarily influenced by climate (model variable: air temperature) and shading (model variable: riparian vegetation).

The best model for the small streams of the Mixedwood Plains explained 54% of the variability in stream temperatures with a prediction error of 2.05 °C. This finding matches the performance of other regional studies that have shown predictive errors between 2–3 °C (Appendix B; Wehrly et al. 2009). The large river model explained 75% of the variation in stream temperatures with a prediction error of 1.03 °C. To our knowledge, this level of accuracy has only been achieved in a study by Isaak et al. (2017) in which a spatial statistic network model and high-density stream temperature data were used. Overall, we were successful in developing robust models that are more comprehensive than previous modelling attempts.

The importance of stream size

Our approach for building the models was driven by knowledge of the processes, patterns, and scales influencing stream temperature. Through our exploratory analysis, we detected outliers and inaccuracies in the spatial data and developed better assumptions of the relationships between the spatial data and stream temperature. We found distinctive patterns in the data based on catchment areas of streams. Small drainages are influenced by a variety of local factors. Small streams encompass small areas and thus can be 100% within a type of geology or landcover. This feature means small streams have a great diversity of habitat types and characteristics. As stream size increases, reach contributing areas and upstream catchments encompass larger areas and their characteristics become increasingly more similar and average. Temperatures in larger streams (>700 km^2 drainage area) are driven by fewer factors, primarily air temperature and riparian shading. These distinctive patterns reflect differences in processes governing stream temperature of different sizes of streams. Developing models based on the size of the streams enabled us to reduce the complexity during modelling and increase our accuracy for larger streams to levels not typically found when modelling stream temperature. In contrast to the large stream model, the small stream model had six explanatory variables. As far as we know this approach had not been used before.

Small headwater streams contributed significantly to basin-scale biodiversity through high levels of among-site habitat variation across stream networks (Finn et al. 2011). Headwater streams are diverse in characteristics because they often drain specific types of landscape, not the average condition of a larger area (Wiens 1989). The extremes associated with headwater streams have led to difficulties in modelling. Seelbach et al. (2011) noted how regression models predict the central tendency of data well but often fail in predicting extremes. They further note that small catchments are very abundant in river networks and suffer prediction errors as they often have homogeneous landscape characteristics and are not well-represented by gauged data from long-term monitoring sites.

It is perhaps unsurprising that model performance for small streams was not as good as that for larger systems as small streams are highly sensitive to local conditions, exhibiting high variability in stream temperature in heterogenous landscapes. Due to the low spatial resolution of the data used to develop the models (i.e., 30 m grid cells), landscape heterogeneity may not have been completely differentiated to allow for all the variability of small streams to be explained. A lack of accurate data describing the degree of riparian shading by different vegetation types and the groundwater flow through hyporheic exchange, fracture flow faults and aquifer fed springs may have contributed to errors in the model. Stream temperatures have been observed to be highly variable at reach scale (Ebersole et al. 2003, Arscott et al. 2005, Moore et al. 2005) and as a result, high accuracy data are required to resolve the landscape heterogeneity in small streams. In addition, like all spatial data, the data used in this study will have a degree of intrinsic error in spatial location and/or assigned attributes. These errors may have limited the predictive performance of the model. In contrast, the spatial data resolution was adequate for modelling the variability of large rivers, accounting for differences in model performance.

Thermal classification

Water temperature, or more broadly the thermal regime of streams, is important in sustaining the ecological integrity of aquatic ecosystems. Water temperature influences the distribution and abundance of aquatic species (Caissie 2006). A good understanding of the thermal regime of streams and rivers is needed to effectively manage fisheries and assess environmental impact. The classification of streams by thermal regimes supports understanding of spatial patterns of aquatic biota (e.g., fishes) both longitudinally and regionally. We developed a probability approach to determine the thermal class of streams based on their historical distribution of yearly predicted stream temperatures. This approach enabled us to determine the most likely thermal class of streams by accounting for their temporal variability for the past 30 years and by incorporating uncertainty due to the use of probabilities. Mapped results showed high coincidence between thermal classes and different geological landforms, land use, and topography as expected. This spatial thematic classification can be used to guide biologists unfamiliar with an area of interest.

Future research should explore how the different classes relate to fish presence and absence, and fish communities. Jones and Schmidt (2019) provide an overview on understanding stream temperature and its classification. Fish are highly dependent on water temperature to maintain important biochemical, physiological, and life history processes. Although fish have well defined preferences, they can inhabit a range of temperatures, several degrees warmer than their preferred temperature. How much warmer depends on the duration of exposure, availability of food resources, and their ability to find cooler patches of water. Although fish may seek cooler water during periods of high temperatures in summer, for the remaining 8 to 11 months of the year temperature is not limiting and they can move freely in the stream network or into neighbouring lakes. In winter, fishes may move into warmer water to find overwintering habitat. In areas without barriers, fish can exploit the spatial variation in stream temperatures across the network to maximize fitness. Given the complex nature of stream temperature, a misconception is that coldwater fishes will only be observed in coldwater streams. In fact, some coolwater streams support the highest biomass and production of trout (Lyons et al. 2009). Stream temperature is just one of several determinants of brook trout (*Salvelinus fontinalis*) presence/absence and does not directly predict brook trout occupancy. To protect brook trout, a model is needed that directly predicts their occurrence. This information can be used to strategically prioritize field activities (e.g., electrofishing, eDNA) to focus on streams with higher probabilities of occurrence to confirm presence/absence of fishes.

Using and interpreting temperature/class predictions

The predictions made in this research are not a substitute for empirical data. The maps can provide guidance on what to expect for a stream reach. The maps may also help guide sampling efforts in the field, particularly in areas with uncertainty/lack of knowledge.

The predictions for stream temperature do not provide baseline conditions for making comparisons of what should be or that collected via field-based monitoring programs. The predictions are based on 30-year averages that is different than a particular year, which could be dry and hot or wet and cold. The annual variability for average July temperatures among 78 streams in Ontario was 3.5 °C with a low of 1.2 to a high of 7.6 °C. This means that, on average from one year to the next, stream temperature may vary by 3.5 °C.

Stream temperature predictions below lake outlets should be interpreted with caution as lakes will often be substantially warmer than a stream not draining a lake given the same landscape characteristics. This difference occurs because lake surface temperatures are strongly related to air temperature and elevation (Bachmann et al. 2018). As a result, reaches directly downstream of lakes may be much warmer than predicted. The magnitude of the difference has a regional component and depends on spatial scale. For example, air temperatures naturally decrease towards northern latitudes, which means that lake surface temperatures will also naturally be lower. As a result, predicted stream temperature in the absence of a lake will differ less from the true lake outflow temperature at more northern latitudes. Furthermore, as drainage size increases the processes driving stream temperatures begin to approximate the process governing lake surface temperatures (e.g., air temperature becomes increasingly important). As a result, the difference in predicted vs. actual temperatures will decrease as drainage size increases. To prevent misinterpretation, the AEC framework provides a measure of lake influence effects for each reach that can be used to flag reaches where the true thermal classification may differ from the predicted value as a result of lake effects.

Next steps

The models developed in this study are useful for predicting July average stream temperatures for contemporary conditions and for classifying streams by their thermal regime. While these models are only for the small streams of the Mixedwood Plains and large rivers across Ontario, we will continue to develop temperature models for small streams of the other ecozones (e.g., Ontario Shield and Hudson Bay Lowlands). Thermal classifications can be used in conjunction with aquatic species data to effectively inventory, monitor, and manage Ontario’s streams.

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Appendix A. Overview of stream temperature data cleaning stages

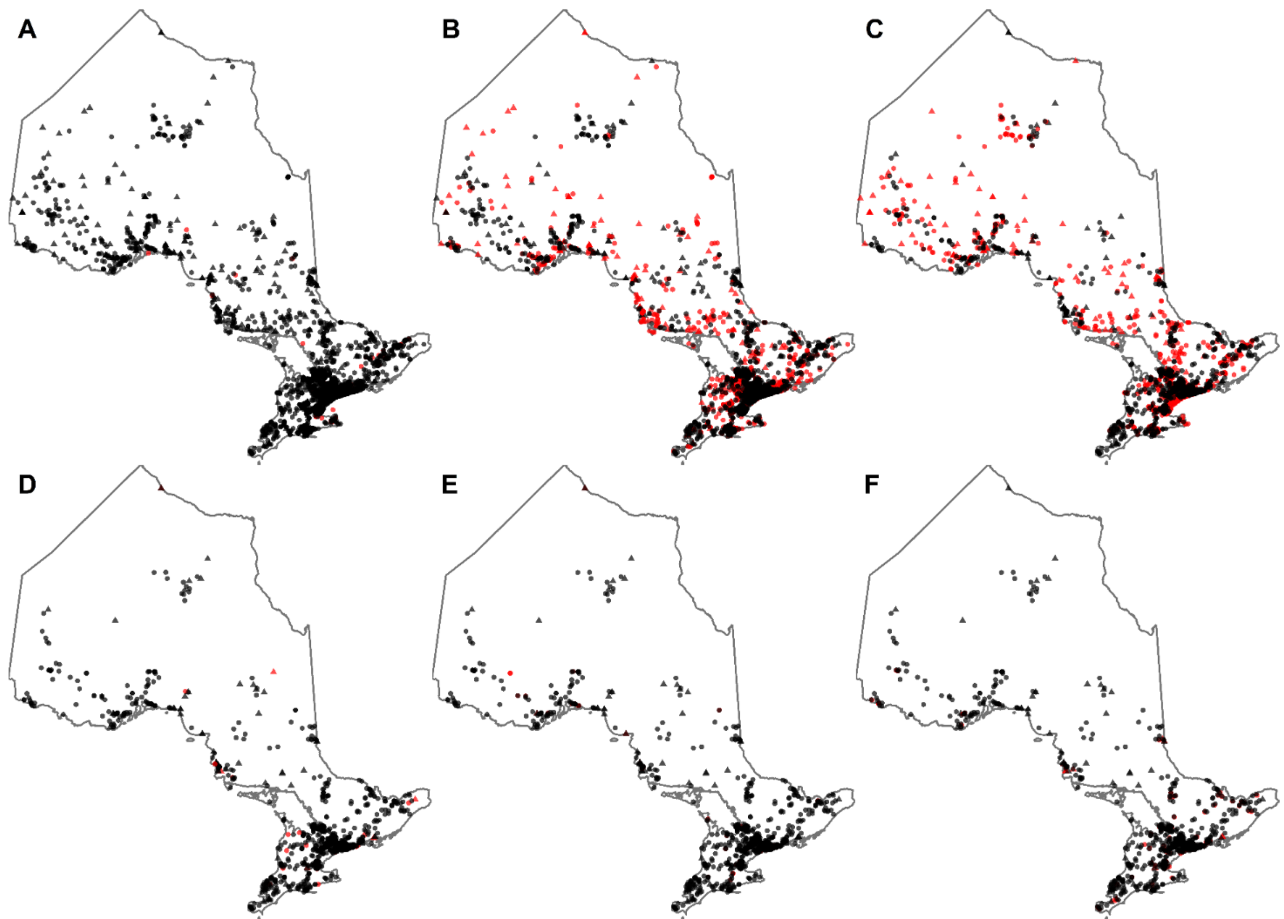

Figure A.1. Overview of stream temperature data cleaning stages applied in this Ontario study: removal of (A) stations with incorrect coordinates, (B) years with incomplete records or bad data, (C) urbanized/lake influenced stations, (D), years with poor air-water relationships, (E) duplicate years of data, and (F) spatially autocorrelated reaches. Circles represent stations used to model small rivers while triangles represent stations used to model large rivers. Red colouration indicates that all remaining data was removed at that cleaning stage.

Appendix B. An overview of broad-scale stream temperature modelling approaches found in the primary literature and their accuracy

Table A.1. Examples of broad-scale stream temperature modelling approaches found in the primary literature and their accuracy. (R2=coefficient of determination; RMSE=root mean square error; NA=not applicable)

Author and region	Months of interest and number of sites	Method(s)	Variables	Best model		Validation	
				R2	RMSE	R2	RMSE
Wehrly et al. 2006 Lower Peninsula of Michigan	July (mean), 1989–2002 282	Stepwise multiple linear regression	Air temperature, sampling station latitude, drainage area, reach-scale slope, groundwater velocity and forest buffer, catchment-scale coarse geology, lakes, wetlands, urban and agriculture	0.64	NA	NA	NA
Wehrly et al. 2009 Michigan and Wisconsin	July (mean) 820 (Michigan) 311 (Wisconsin)	Generalized additive model, ordinary kriging, mixed linear regression and linear mixed model	Air temperature, drainage area, catchment scale forest, slope, soil permeability and water	NA	2.0–2.95	NA	NA
Jones et al. 2014 Flathead River Basin, Canada and USA	August (mean), 1998–2010 201	Fixed effect GLM and geostatistical models (spatial flow routed and spatial hierarchical)	Air temperature, stream flow, elevation, slope, aspect, latitude, longitude, solar radiation, lake effect	0.82	1.27	0.48	1.90
Detenbeck et al. 2016 Northeastern USA	July and August (median) 987	Mixed spatial statistical model	Air temperature, lake epilimnion, reach-scale mean discharge, slope, area-weighted air temperature and velocity, catchment-scale surrogates of groundwater input, urban heat island metrics, topographic solar shading and riparian shading	1.67	1.4–1.5	NA	NA
Isaak et al. 2017 Western USA	August (mean), 1993–2011 > 22,700	Spatial statistical model	Air temperature, drainage area, elevation, reach slope, northing, annual precipitation, discharge, riparian canopy, catchment-scale lake and glacier	0.91	1.1	NA	NA
Mauger et al. 2017 Cook Inlet Basin, Alaska	July (mean), 2008–2012 92	Linear mixed effects and multiple regression	Percent wetlands, forested, and open water, maximum and mean watershed elevation, logger site elevation, mean watershed slope, watershed area, stream gradient, lake influence, air temperature, mean annual discharge, permeable geology cover	0.60	1.71	NA	NA

Appendix C. Aggregation of aquatic ecosystem classification variables

Table A.2. Aggregation of Aquatic Ecosystem Classification variables for modelling. For methods and details of the input variables, refer to Jones and Schmidt (2017).

Input variable	Model class
Aspect SE	*Aspect*
Aspect S	*Aspect*
Aspect SW	*Aspect*
Marsh	*Wetland*
Swamp	*Wetland*
Fen	*Wetland*
Bog	*Wetland*
Heath	*Wetland*
Treed peatland	*Treed*
Upland treed	*Treed*
Deciduous treed	*Treed*
Mixed treed	*Treed*
Coniferous treed	*Treed*
Cultivated treed	*Treed*
Hedge row	*Treed*
Tall grass woodland	*Treed*

Appendix D. Temperature preferenda for Ontario fish species

Table A.3. Final temperature preferenda (FTP) for 88 fish species commonly found in Ontario's flowing waters. Temperature preferenda are derived from Hasnain et al. (2013).

Cold-water		Cool-water		Warm-water	
Common name	**FTP**	**Common name**	**FTP**	**Common name**	**FTP**
Round whitefish	8.3	White crappie	19.1	Smallmouth bass	25.0
Sea lamprey	10.3	Emerald shiner	19.3	Northern redbelly dace	25.3
Lake sturgeon	11.0	Blacknose dace	19.6	Rosyface shiner	25.3
Slimy sculpin	11.0	Sauger	19.6	Green sunfish	25.4
Rainbow smelt	11.2	American eel	19.9	Bighead carp	25.4
Longnose sucker	11.4	Rainbow darter	19.9	Muskellunge	25.4
Lake trout	11.8	Rainbow darter	19.9	Chain pickerel	25.5
Lake herring, cisco	12.4	Redfin shiner	20.5	Grass pickerel	25.7
Threespine stickleback	12.5	Northern pike	20.7	Brown bullhead	26.2
Lake whitefish	12.7	Brook stickleback	21.3	Fathead minnow	26.6
Pink salmon	13.0	river chub	21.7	Shorthead redhorse	26.8
Burbot	13.2	Spotted sucker	21.8	Northern hog sucker	27.0
Trout-perch	13.4	Golden shiner	21.8	Lake chub	27.0
Sockeye salmon	13.7	Common shiner	21.9	Grass carp	27.1
Chinook salmon	13.8	Fallfish	22.0	Channel catfish	27.3
Chum salmon	14.1	Longear sunfish	22.5	White bass	27.3
Coho salmon	14.4	Walleye	22.5	Longnose gar	27.4
Brook trout	14.8	Tessellated darter	22.8	Spotfin shiner	27.5
Longnose dace	15.3	Johnny darter	22.8	Pumpkinseed	27.7
Stonecat	15.3	Banded killifish	23.0	Carp	27.7
Atlantic salmon	15.3	Redear sunfish	23.1	Mooneye	28.0
Rainbow trout	15.5	White sucker	23.4	Yellow bullhead	28.2
Brown trout	15.7	Black crappie	23.4	Largemouth bass	28.6
Atlantic sturgeon	16.0	Roundtail chub	23.8	White perch	29.8
Spotted gar	16.0	Central stoneroller	23.9	Bluegill	30.0
Mottled sculpin	16.2	Bluntnose minnow	24.1	Bowfin	30.0
Pugnose shiner	16.5	Finescale dace	24.1		
Ninespine stickleback	16.5	Brook silverside	24.5		
Spottail shiner	16.6	Eastern sand darter	24.6		
Yellow perch	17.6	Freshwater drum	24.6		
		Rock bass	24.9		
		Creek chub	24.9		

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ISBN 978-1-4868-4956-7 (pdf)